
AWS
re:Invent
NOV. 28 – DEC. 2, 2022 | LAS VEGAS, NV

AIM408

Driving impact through cutting-edge research with the Amazon Research Awards

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AWS AI

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Professor
University of Maryland

Jon Tamir (he/him)

Assistant Professor
The University of Texas at Austin

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Agenda

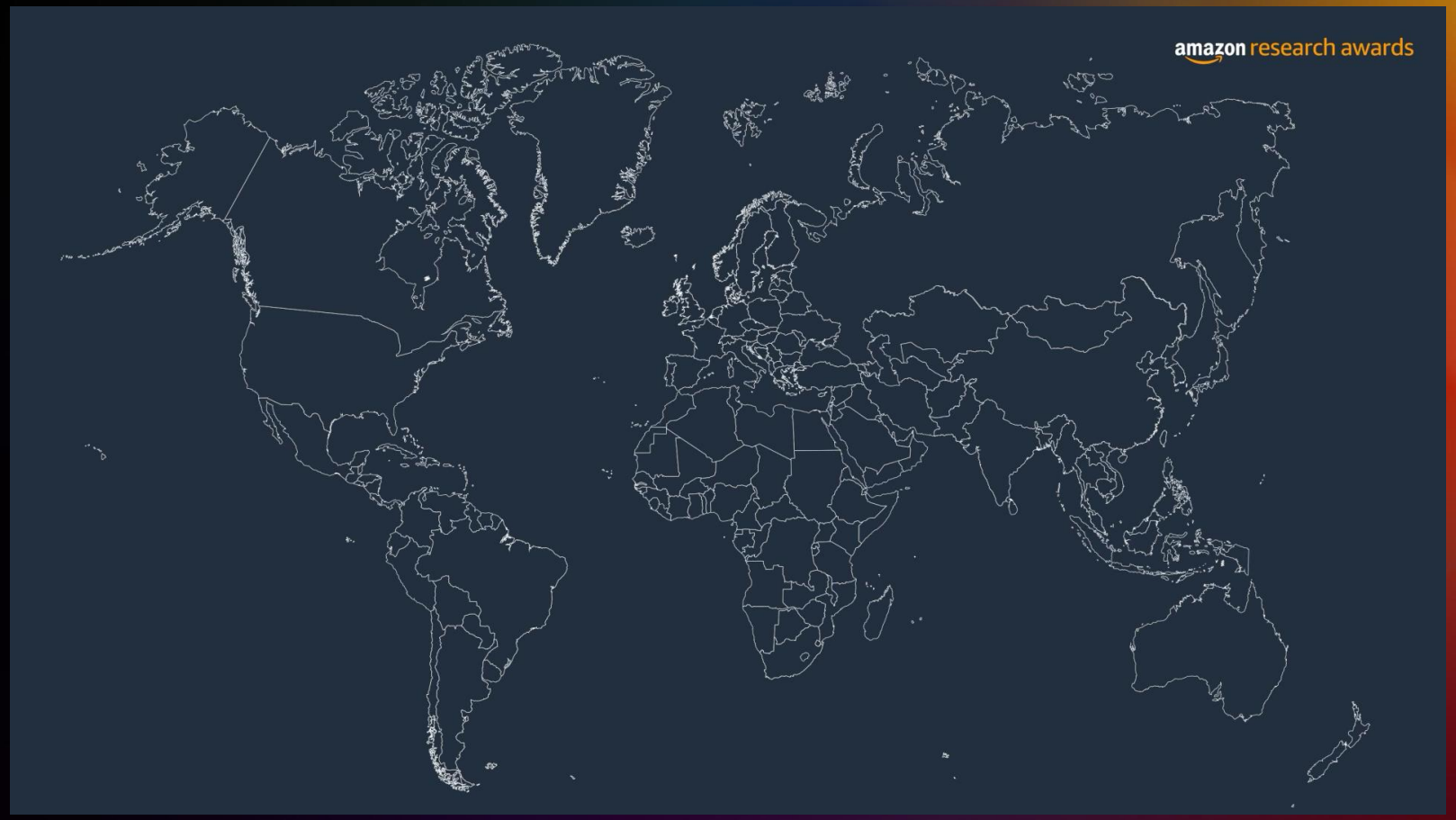
- Mission of the Amazon Research Awards program
- Philip Resnik on Mental Health and AI: From language analysis to clinical utility
- Jon Tamir on Robust Magnetic Resonance Imaging with Deep Learning

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The Amazon Research Awards program supports research to advance state-of-the art, “customer-obsessed” science.

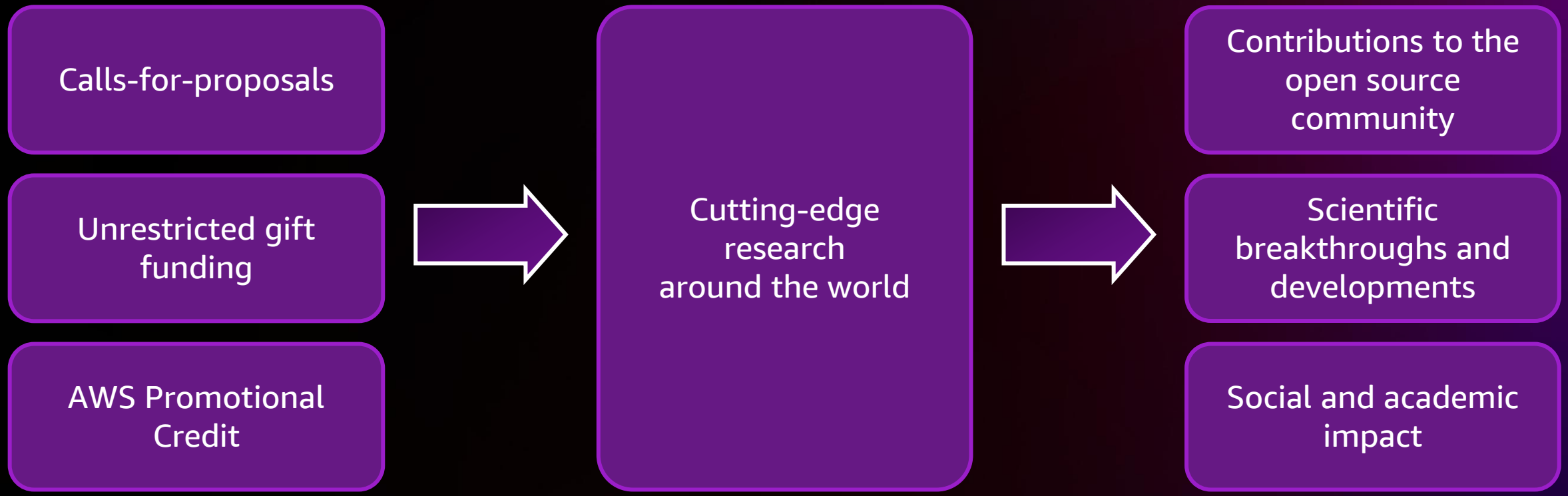
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Amazon Research Awards around the world



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The ARA Cycle



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Machine Learning enables researchers to pursue major real-world problems that were previously thought to be unsolvable.

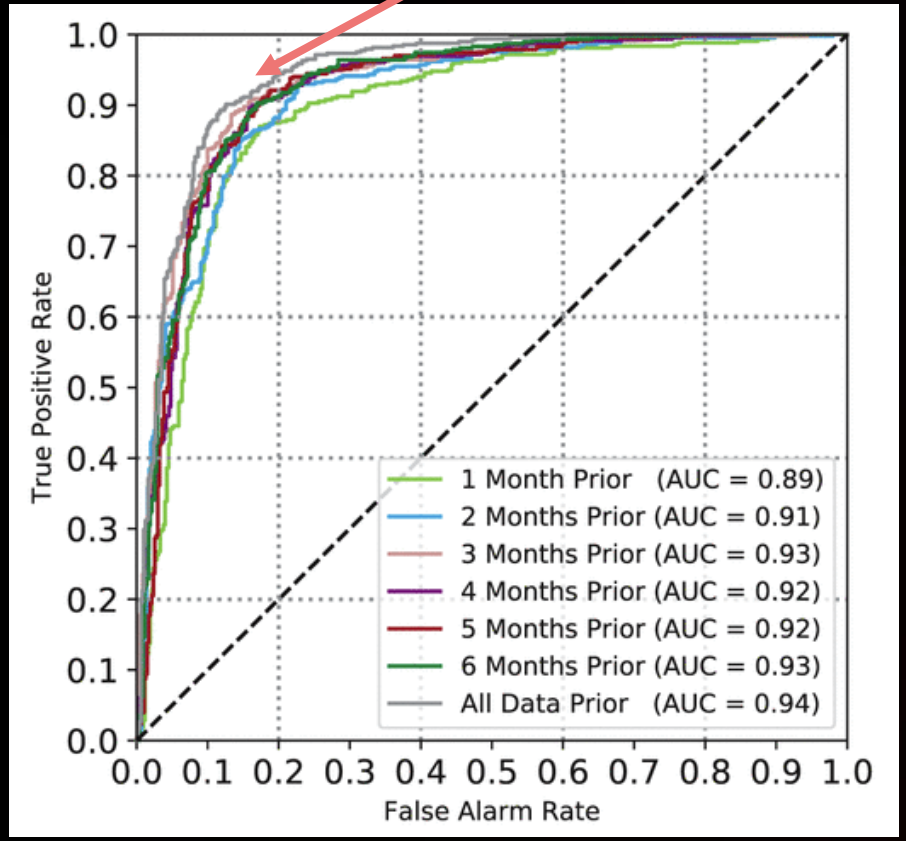
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Mental Health and AI: From language analysis to clinical utility

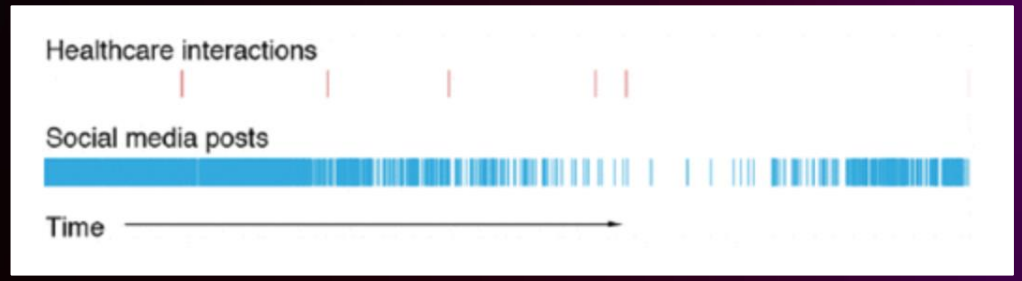
Philip Resnik (he/him)
MPower Professor
Professor, Institute for Advanced Computer Studies and Department of Linguistics
University of Maryland

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90-95% true positives,
With only 10-20% false positives



Coppersmith, Glen, et al. "Natural language processing of social media as screening for suicide risk." Biomedical informatics insights 10 (2018): 1178222618792860.



- Predicting attempts better than clinicians
- Ethical social media collection via data donation*
- *Events*, not ratings or proxy variables**

*Benton, Adrian, Glen Coppersmith, and Mark Dredze. "Ethical research protocols for social media health research." Proceedings of the first ACL workshop on ethics in natural language processing. 2017.

*Chancellor, Stevie, et al. "A taxonomy of ethical tensions in inferring mental health states from social media." Proceedings of the conference on fairness, accountability, and transparency. 2019.

**Cf. Ernala, Sindhu Kiranmai, et al. "Methodological gaps in predicting mental health states from social media: triangulating diagnostic signals." *Proceedings of the 2019 CHI conference on human factors in computing systems*. 2019.

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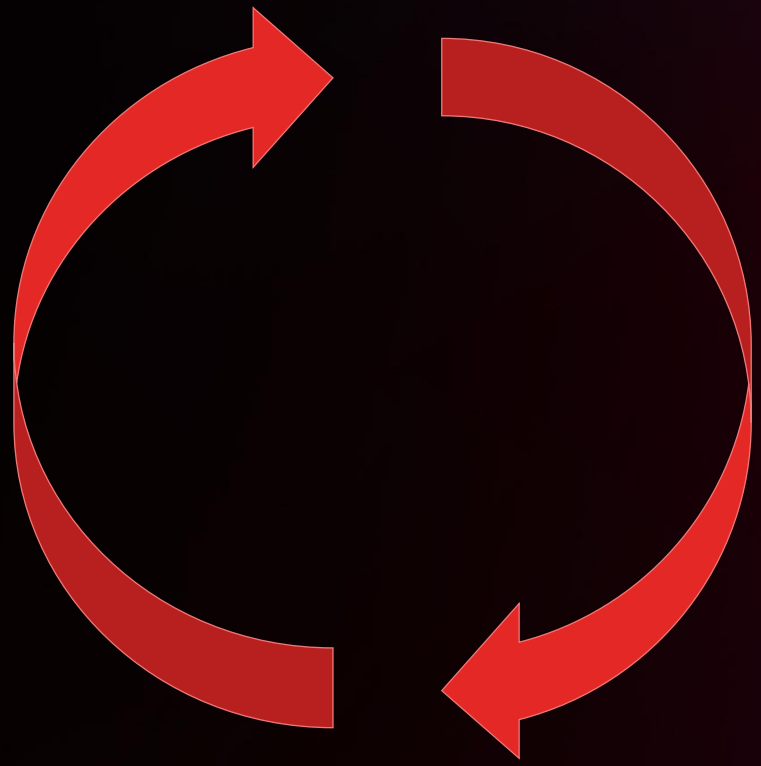
Then what?*

*Resnik, P., Foreman, A., Kuchuk, M., Musacchio Schafer, K., & Pinkham, B. (2021). Naturally occurring language as a source of evidence in suicide prevention. *Suicide and Life-Threatening Behavior*, *51*(1), 88-96

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Domain experts

What's possible?



What's needed?

Technologists

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What's possible?
Matching needs with solutions

Obtaining the data needed to advance the te

Moving from *classification* to *prioritization*

Gaining insights from lived experiences



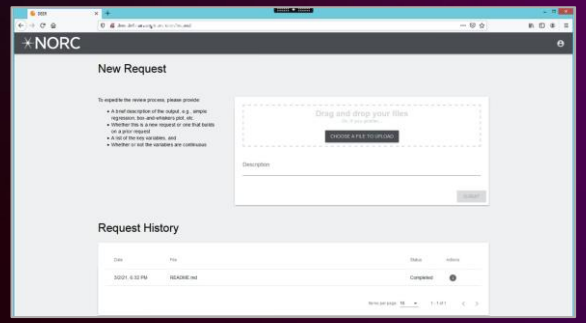
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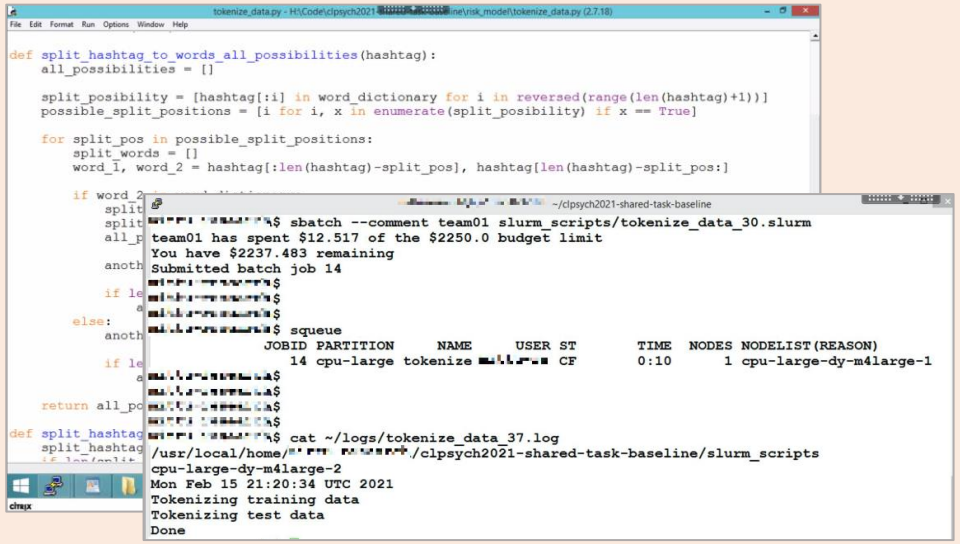
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Bringing researchers to data











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Macavaney, S., Mittu, A., Coppersmith, G., Leintz, J., & Resnik, P. (2021). Community-level research on suicidality prediction in a secure environment: Overview of the CLPsych 2021 shared task. In *Proceedings of the Seventh Workshop on Computational Linguistics and Clinical Psychology: Improving Access* (pp. 70-80).

What's possible?
Matching needs with solutions

Obtaining the data needed to advance the technology

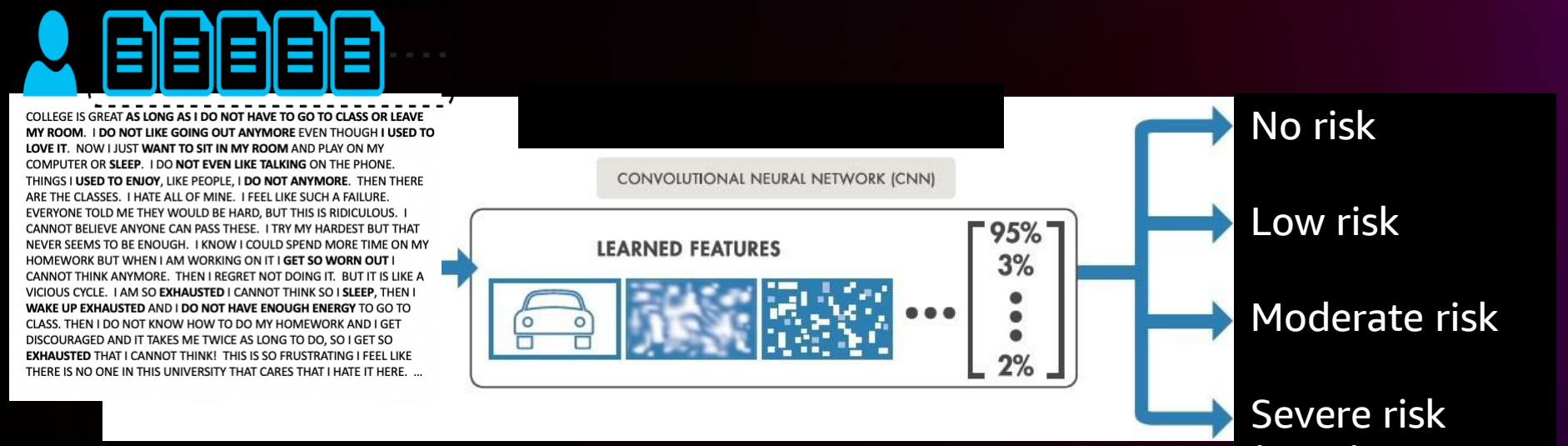
Moving from *classification* to *prioritization*

Gaining insights from lived experiences

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From classification to prioritization

***TECHNOLOGY*-CENTRIC VIEW OF THE PROBLEM**



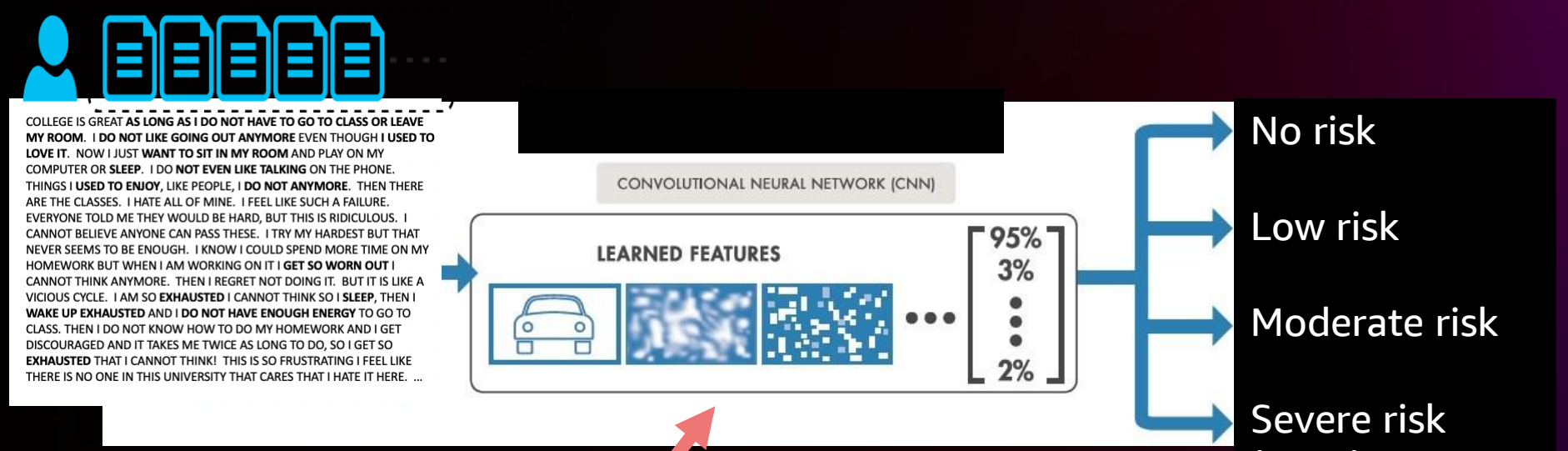
Shing, Han-Chin, Philip Resnik, and Douglas W. Oard. "A prioritization model for suicidality risk assessment." In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 8124-8137. 2020. (Also applies to subsequent slides)

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https://medium.com/intro-to-artificial-intelligence/simple-image-classification-using-deep-learning-deep-learning-series-2-

From classification to prioritization

TECHNOLOGY-CENTRIC VIEW OF THE PROBLEM



It's usually hard or impossible to understand what features were used – *why* labels are chosen.

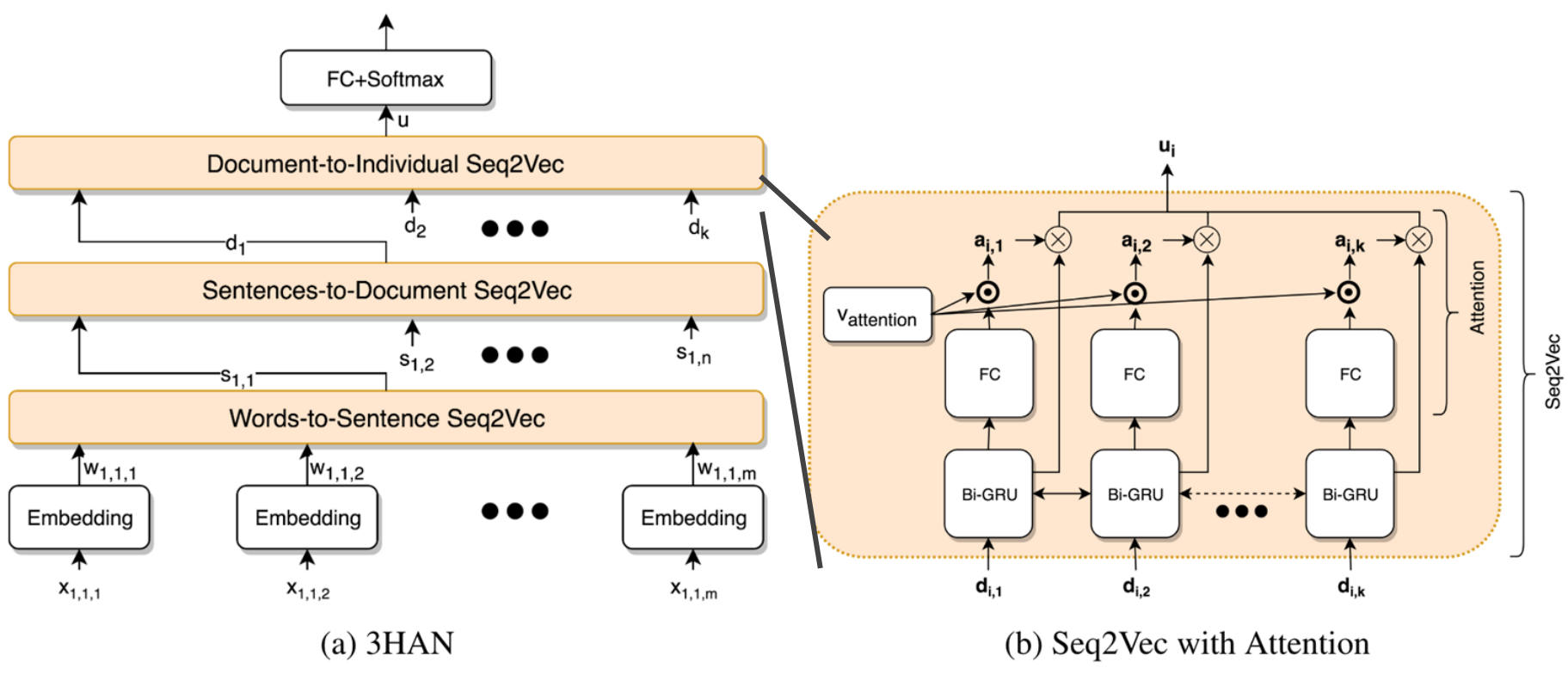
Labels alone don't provide within-risk-level ranking

https://medium.com/intro-to-artificial-intelligence/simple-image-classification-using-deep-learning-deep-learning-series-2-5e5b89e97926

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3-Level Hierarchical Attention Network (3HAN)

From classification to prioritization

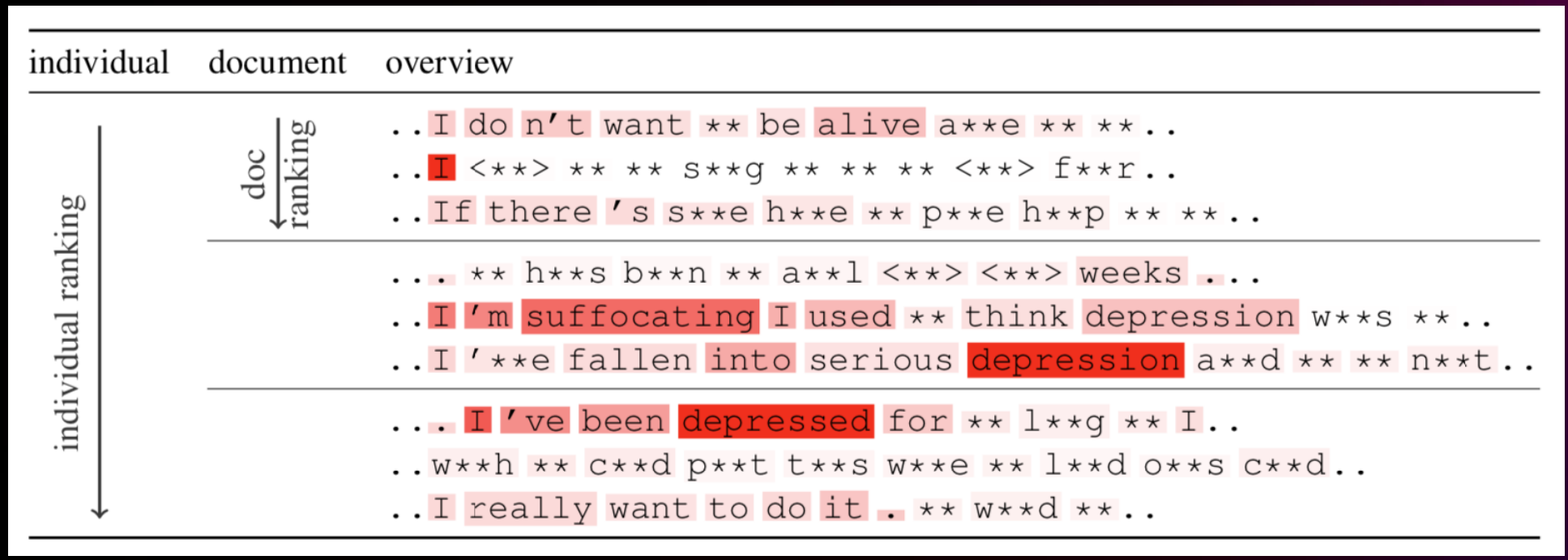


Shing, Han-Chin, et al. "Expert, crowdsourced, and machine assessment of suicide risk via online postings." Proceedings of the fifth workshop on computational linguistics and clinical psychology: from keyboard to clinic. 2018. To apply for research access to the dataset see http://users.umiacs.umd.edu/~resnik/umd_reddit_suicidality_dataset.html.

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From classification to prioritization



Example from the University of Maryland Reddit Suicidality Dataset:
1.5M posts from 11,129 Reddit r/SuicideWatch users (plus equal number of control users)
With 242 users annotated as no, low, moderate, or severe risk by suicide prevention experts

Shing, Han-Chin, et al. "Expert, crowdsourced, and machine assessment of suicide risk via online postings." Proceedings of the fifth workshop on computational linguistics and clinical psychology: from keyboard to clinic. 2018. To apply for research access to this dataset see http://users.umiacs.umd.edu/~resnik/umd_reddit_suicidality_dataset.html.

Although the original posts are anonymous, since they are public social media content, we have obfuscated non-essential text here as a further caution to protect privacy.

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What's possible?
Matching needs with solutions

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We can use language technology to get a much richer picture of people's lived experience!

Philip Resnik, technological optimist

Every lived experience is an N of 1.

Rebecca Resnik, clinical psychologist

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Working top-down

Looking for evidence through the lens of known categories/constructs/patterns

"[Despair], owing to some evil trick played upon the sick brain by the inhabiting psyche, comes to resemble the diabolical **discomfort** of being **imprisoned** in a fiercely **overheated** room. And because no breeze stirs this cauldron, because there is no escape from this **smothering confinement**, it is entirely natural that the victim begins to think ceaselessly of oblivion."

— Dr. Kay Redfield Jamison, *Night Falls Fast: Understanding Suicide*

Entrapment

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Schuck, Allison; Calati, Raffaella; Barzilay, Shira; Bloch-Elkouby, Sarah; Galynker, Igor (May 2019). "Suicide Crisis Syndrome: A review of supporting evidence for a new suicide-specific diagnosis". Behavioral Sciences & the Law. 37 (3): 223–239. doi:10.1002/bsl.2397.

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Entrapment

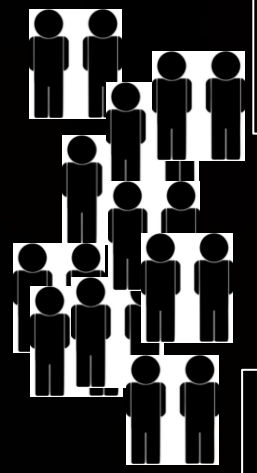
Schuck, Allison; Calati, Raffaella; Barzilay, Shira; Bloch-Elkouby, Sarah; Galynker, Igor (May 2019). "Suicide Crisis Syndrome: A review of supporting evidence for a new suicide-specific diagnosis". Behavioral Sciences & the Law. 37 (3): 223–239. doi:10.1002/bsl.2397.

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Working bottom-up with language

Discovering implicit categories using topic modeling (Blei et al., 2003)



i hate money. it's a form of slavery. i hope i die soon, get in car crash, or get cancer or die from aids so i can be in peace.sucks to be still alive.

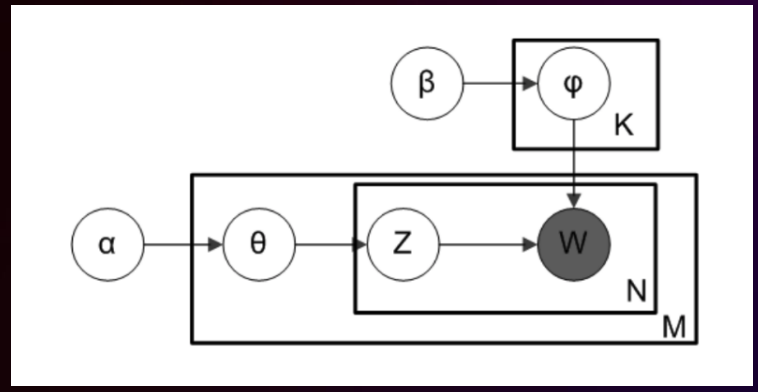
So, I don't know if Im depressed or if im just slow or what, but these last few years have been the worst. Im 18, a senior in high school, but I just dont feel real anymore. Im so awkward that i cant talk to my parents or my friends, ive realized that i dont really know anyone.

I failed all of my classes in college last semester and fasfa is no longer available to me due to my failure. I lied to my parents about this. I feel that if they found out about this I would be without a hom

I am a 24m. 2 months ago I lost the woman I loved more than anything in this world. Our 6yr 8month relationship just thrown away. I was lied to for the last year of it and she also cheated on me at least once.

	word 1	word 2		word N
item 1	value 1	value 2		value N
item 2	value 1	value 2		value N
item 3	value 1	value 2	...	value N
item 4	value 1	value 2		value N
...				

Pr(word w | topic z)



Pr(topic z | item i)

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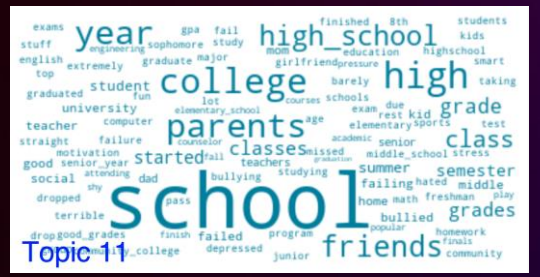
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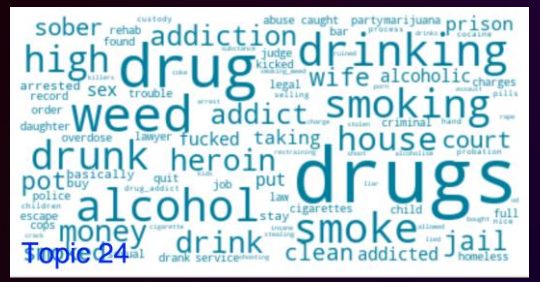
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	word 1	word 2		word N
item 1	value 1	value 2		value N
item 2	value 1	value 2		value N
item 3	value 1	value 2	...	value N
item 4	value 1	value 2		value N
...				

Topic 11	text
0.48050353	So, I'm a poor student (~2.8 GPA) at a good school. I've been talking to my college guidance counselor about colleges that I'd be able to get into ar
0.47767672	Today I skipped school.....Got yelled at by my parents. Got compared to one of my actual friends..... My dad basically called me worthless. I starte
0.45305499	Now matter how hard I try I don't think I can escape this depression. It all started over a fucking girl. Now I'm just seeing the negative side to ever
0.43119257	and I don't know what to, everyone including me expects me to go to college and now thanks to my shitty grades from my senior year I might not
0.39189101	I just feel like every area of my life is falling apart. My personal and professional life leads to nothing but stress. My physical health is falling apart.
0.38730073	I'm considering suicide. I have struggled with depression and anxiety in the past, but right now I'm decently happy.I just dropped out of college, be





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Example: Inferring population-specific categories from language

Notes	Valence	Regression value	Top 20 words
social engagement	p	-1.593	game play football team watch win sport ticket texas season practice run basketball lose so
social engagement	p	-1.122	music song listen play band sing hear sound guitar change remind cool rock concert voice
social engagement	p	-0.89	party night girl time fun sorority meet school house tonight lot rush drink excite fraternity
social engagement	p	-0.694	god die church happen day death lose doe bring care pray live plan close christian control f
high emotional valence	e	-0.507	hope doe time bad wait glad nice happy worry guess lot fun forget bet easy finally suck fin
somatic complaints	n	-0.205	cold hot hair itch air light foot nose walk sit hear eye rain nice sound smell freeze weather
poor ego control; immature	n	0.177	yeah wow minute haha type funny suck hmm guess blah bore gosh ugh stupid bad lol hey s
relationship issues	n	0.234	call talk miss phone hope mom mad love stop tonight glad dad weird stupid matt email any
homesick; emotional distress	n	0.34	home miss friend school family leave weekend mom college feel parent austin stay visit lo
social engagement	p	0.51	friend people meet lot hang roommate join college nice fun club organization stay social to
negative affect*	n	0.663	suck damn stupid hate hell drink shit fuck doe crap smoke piss bad kid drug freak screw cr
high emotional valence	e	0.683	life change live person future dream realize mind situation learn goal grow time past enjoy
sleep disturbance*	n	0.719	sleep night tire wake morning bed day hour late class asleep fall stay nap tomorrow leave n
high emotional valence	e	0.726	love life happy person heart cry sad day feel world hard scar perfect feeling smile care stro
memories	n	0.782	weird talk doe dog crazy time sad stuff funny haven happen bad remember day hate lot sca
somatic complaints*	n	0.805	hurt type head stop eye hand start tire feel time finger arm neck move chair stomach bother
anxiety*	n	1.111	feel worry stress study time hard lot relax nervous test focus school anxious concentrate pr
emotional discomfort	n	1.591	feel time reason depress moment bad change comfortable wrong lonely feeling idea lose g
homesick; emotional distress*	n	2.307	hate doe sick feel bad hurt wrong care happen mess horrible stupid mad leave worse anym

Supervised LDA topics from undergraduate stream-of-consciousness essays identified by a clinician as most relevant for assessing depression. Supervision (regression) is based on Z-scored Big-5 scores for emotional instability (neuroticism).

Resnik et al., Beyond LDA: Exploring Supervised Topic Modeling for Depression-Related Language in Twitter. NAACL Workshop on Computational Linguistics and Clinical Psychology, Denver, CO, June 2015.

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sleep disturbance*	n	0.719	sleep night tire wake morning bed day hour late class asleep fall stay nap tomorrow leave n…
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anxiety*	n	1.111	feel worry stress study time hard lot r…
emotional discomfort	n	1.591	feel time reason depress moment bad…
homesick; emotional distress*	n	2.307	hate doe sick feel bad hurt wrong care…

music song listen play band sing hear… party night girl time fun sorority meet…

sleep night tire wake morning bed day hour late class asleep fall stay nap

hurt type head stop eye hand start tire feel time finger arm neck move chair stomach

feel worry stress study time hard lot relax nervous test focus school anxious

Supervised LDA topics from undergraduate stream-of-consciousness … identified by a clinician as most relevant for assessing depression. Supervision (regression) is based on Z-sc… scores for emotional instability (neuroticism).

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Reasons to Live:
A Thematic Analysis of 16,648 Self-Reports

Collaborative work with Rebecca Resnik, Josh Hagedorn, Katherine Musacchio Schafer, and Jonathan B. Singer

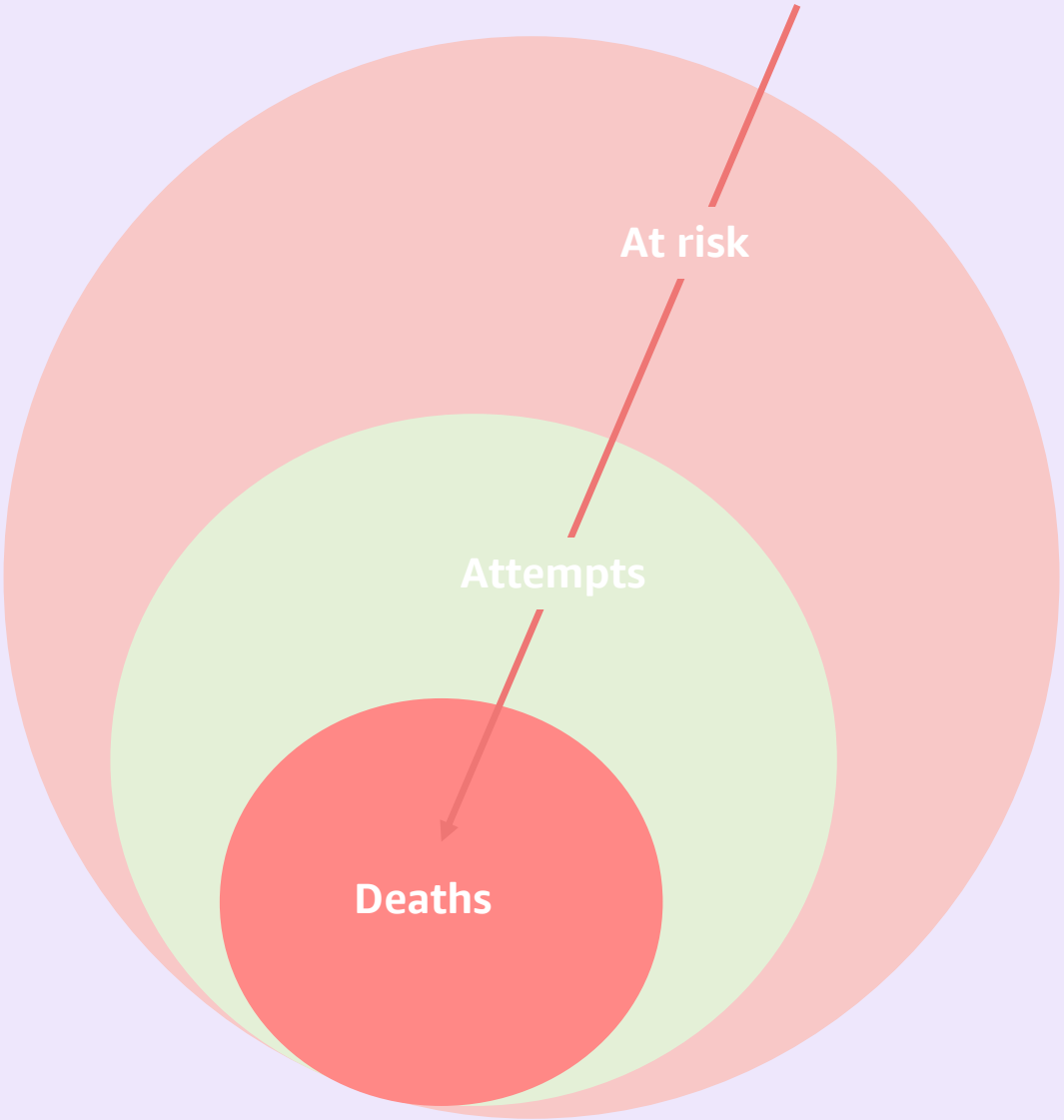
Contributions from April Foreman

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See also: Mason, Andre, et al. "A content analysis of Reddit users' perspectives on reasons for not following through with a suicide attempt." *Cyberpsychology, Behavior, and Social Networking* 24.10 (2021): 642-647.

The majority of suicide research focuses on reasons people die

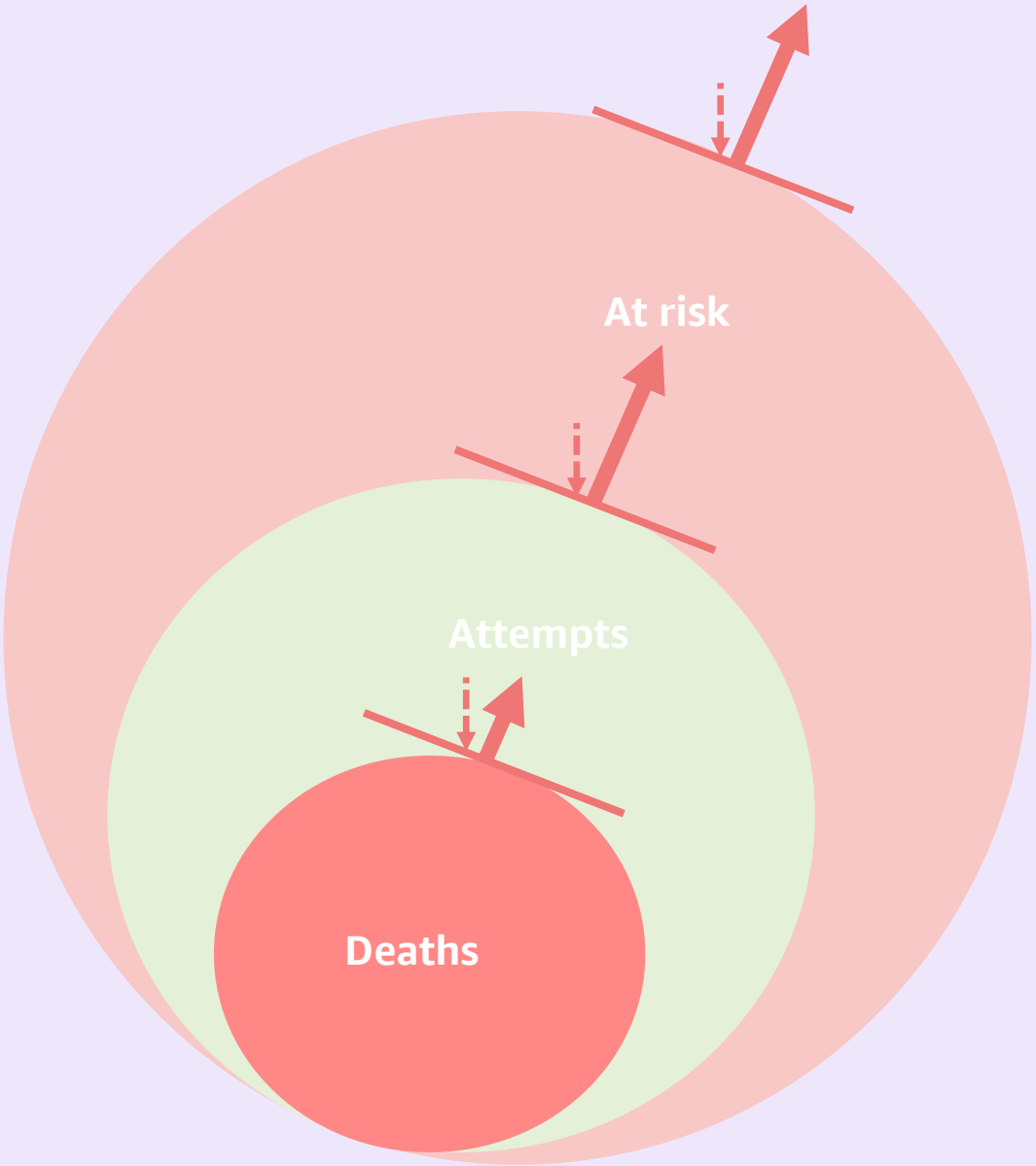
- **Theoretical frameworks**
  - Hopelessness (Beck), Thwarted Belongingness / Burdensomeness (Joiner), …
- **Risk factors**
  - Franklin, Joseph C., et al. "Risk factors for suicidal thoughts and behaviors: A meta-analysis of 50 years of research." Psychological Bulletin 143.2 (2017): 187.
- **Characterizations of crisis/imminent risk**
  - SCS (Galynker et al.), ASAD (Joiner et al.)
- **Predictive machine learning models**
  - Schafer, K. M., Kennedy, G., Gallyer, A., & Resnik, P. (2021). A direct comparison of theory-driven and machine learning prediction of suicide: A meta-analysis. PloS one, 16(4), e0249833.



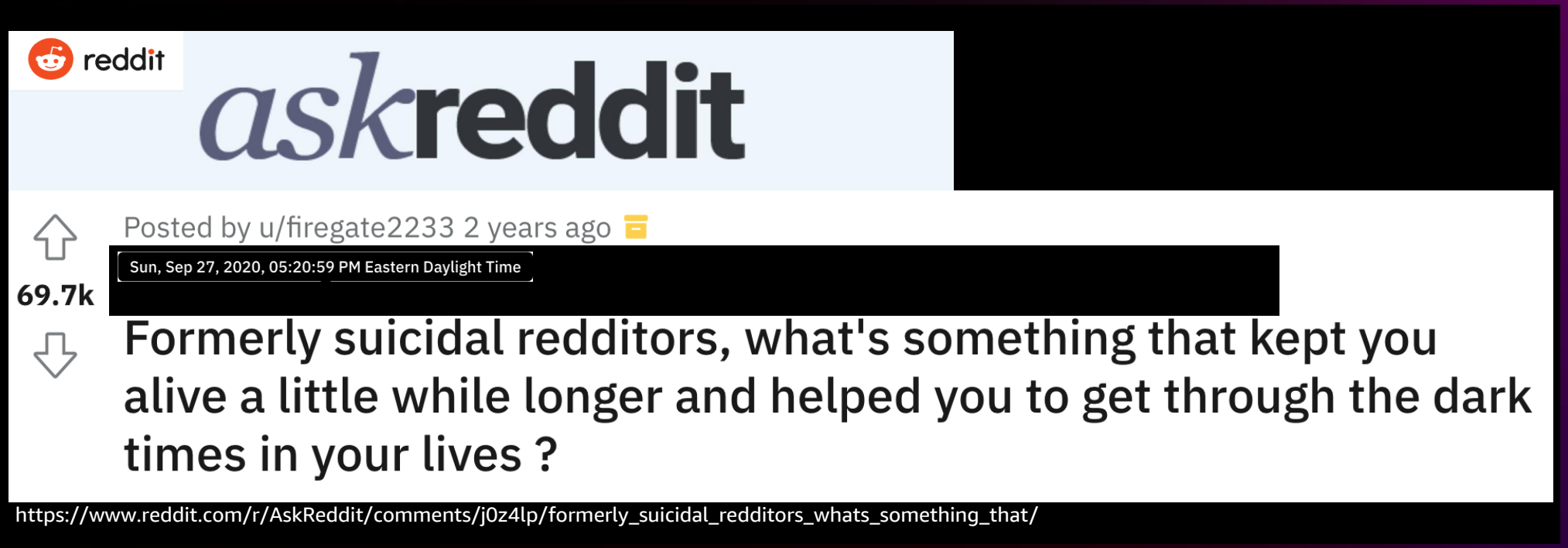
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Reasons people live are less studied

- **Reasons for Living Inventory**
  - Linehan et al., 1983
- **Self-generated reasons for living/dying**
  - Brüdern et al., 2018



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- **Large scale.** About 16,648 responses in the first day.
- **Broad.** A wide range of lived experiences.
- **Current.** A reflection of people's experiences in today's world.

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Computer-assisted content analysis: Topic modeling



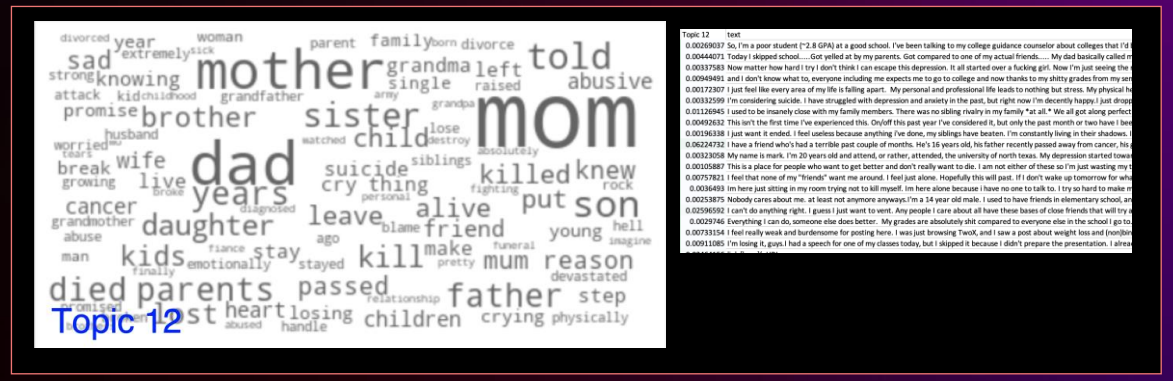
docID	Topic 12	text
4888	0.639	… Decades ago I swore I would not make my parents look at me in a coffin. And I swore I would never leave my son fatherless. That is what kee
11853	0.632	I promised my dad I would never make him cry when I was like 3 years old. I am now 28 and will never break that promise.
8811	0.598	My best friend. We had just lost our mother (her birth mom, who treated me as her own), I knew she couldn't handle losing her and me too. S
13763	0.598	The though of my mother having to lose her youngest child. She is a strong woman but it would break her. My friend had only recently died ag
312	0.596	My mother lost a son 3 years ago I don't want her to lose another.
13453	0.561	My burning desire to not have my mom lose both her father and one of her sons to suicide. That woman has lost enough. I don't want her to t
8937	0.554	I watched my best friend's mother had to be carried out of her son's funeral after he killed himself. I couldn't imagine doing that to my mom. I
1976	0.553	My little sister being left alone with my abusive parents
6558	0.553	Single mom here. Didn't want to leave my daughter alone.

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Resnik, P., Goel, P., Hoyle, A., Sarkar, R., Hagedorn, J., Gearing, M., and Bruce, C. (2022). A Step-by-Step Protocol for Curation of Topic Models by Subject Matter Experts. Presented at Conference on New Directions in Analyzing Text as Data (TADA), New York City, October 6-7, 2022.

Computer-assisted content analysis: Curation by subject matter experts

Specific family members	People were VERY specific about which family members kept them alive. They said things like, "I did not want my MOM, SISTER, DAD, ETC., to blame themselves." "I did not want to leave my grandmother, kids, or siblings, etc. to be without care."



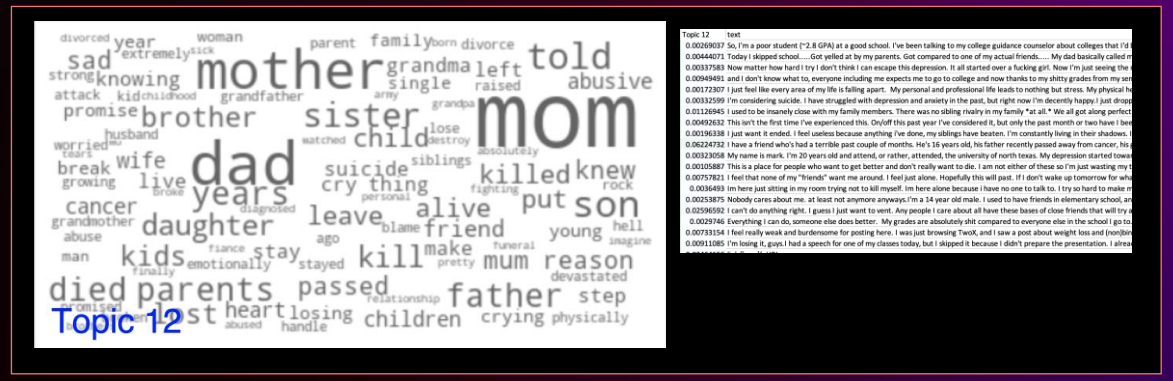
Protect my parents	Empathy for how this will impact one's parents, desire to spare them pain/devastation. "I couldn't do that to my mom/dad."

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Resnik, P., Goel, P., Hoyle, A., Sarkar, R., Hagedorn, J., Gearing, M., and Bruce, C. (2022). A Step-by-Step Protocol for Curation of Topic Models by Subject Matter Experts. Presented at Conference on New Directions in Analyzing Text as Data (TADA), New York City, October 6-7, 2022.

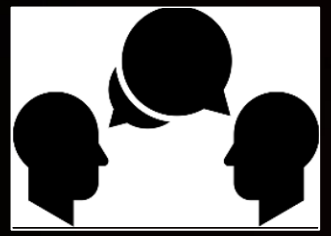
Computer-assisted content analysis: Consensus step

Specific family members	People were VERY specific about which family members kept them alive. They said things like, "I did not want my MOM, SISTER, DAD, ETC., to blame themselves." "I did not want to leave my grandmother, kids, or siblings, etc. to be without care."



Protect my parents	Empathy for how this will impact one's parents, desire to spare them pain/devastation. "I couldn't do that to my mom/dad."

"Consensus" SMEs



→ Not wanting to hurt specific family members

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Resnik, P., Goel, P., Hoyle, A., Sarkar, R., Hagedorn, J., Gearing, M., and Bruce, C. (2022). A Step-by-Step Protocol for Curation of Topic Models by Subject Matter Experts. Presented at Conference on New Directions in Analyzing Text as Data (TADA), New York City, October 6-7, 2022.

Results

Categories emerged that provided insight into how people moved from ideation *away* from suicide attempts.



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Meta-categories

Meta-category 1: Caretaking

Topic	Consolidated Category Label
12	**Not wanting to hurt specific family members**
19	Financial burdens for survivors or if attempt fails
24	Not wanting to traumatize loved ones, especially finding and having to deal with the body
25	Pets, especially cats and dogs -- not wanting to hurt them, worry about them, etc.
30	Not wanting to hurt specific family members, particularly children

I promised my dad I would never make him cry when I was like 3 years old. I am now 28 and will never break that promise.

My dog. I could not stand the thought of my dog wondering why I never came home to him again.

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Meta-categories

Meta-category 2: Positive foresight

Topic	Consolidated Category Label
1	Holding on for one more day and focusing on the next thing, routine, sleep on it and see if/how things get better in the morning
2	Quotes, inspiration, philosophy, wonder -- things that resonate/connect
4	Sense of connection -- feeling seen, heard, understood, cared about by other people
5	Professional diagnosis and treatment
6	Hope and connection with and/or fear, from spiritual or religious beliefs
8	Recognition that suicide is "a permanent solution to a temporary problem" and life will change
10	Hope -- looking past the bad and feeling like life can get better
17	Insight/realization about not wanting to die or finding meaning in surviving an attempt
22	Professional diagnosis and treatment
23	Insights from reading or writing, including writing a suicide note

Even one moment of good in the future would make withstanding this pain/not attempting suicide worth it.

I really want a shrimp boat. I don't have a shrimp boat yet, but if I die, I'll never have a shrimp boat. So, when I want to kill myself, I just remind myself that I'll never get a shrimp boat if I go through with it. As long as I'm working towards it, I feel motivated to keep going on.

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Meta-categories

Meta-category 3: Simple pleasures

Topic	Consolidated Category Label
3	Looking forward to next episodes of TV, new games, experiencing new media
11	Music -- wanting to continue hearing it, experiencing music as meaningful, specific artists
14	Food and sensory pleasures
15	Substance use and abuse
16	Spending time on alternative media
21	Turning point, transition, new connection
26	Finding a new distraction or focus

I just wanted to see the Avengers fight Thanos in the MCU. It sounds silly but having something to look forward to at all can be invaluable when you're in the thick of an episode.

No joke I wanted to watch Game of Thrones season 8.

Weed, cigarettes and Lexapro.

Today was such a nice day. The sun was nice. The rain was cool. The wind was breezy.

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Meta-categories

Meta-category 4: Negative foresight

Topic	Consolidated Category Label
9	Fear of surviving an attempt and being worse off
13	Spite -- proving people wrong

Fear of pain. Fear of surviving. Fear of failure.

For a time it was sheer spite. Living was my vengeance.

Spite. I have to outlive this bastard, I must live long enough to see this megalomaniac die, et cetera.

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Clinical implications



Finding their lifeline:

Don’t miss it, don’t dismiss it

Clinical implications

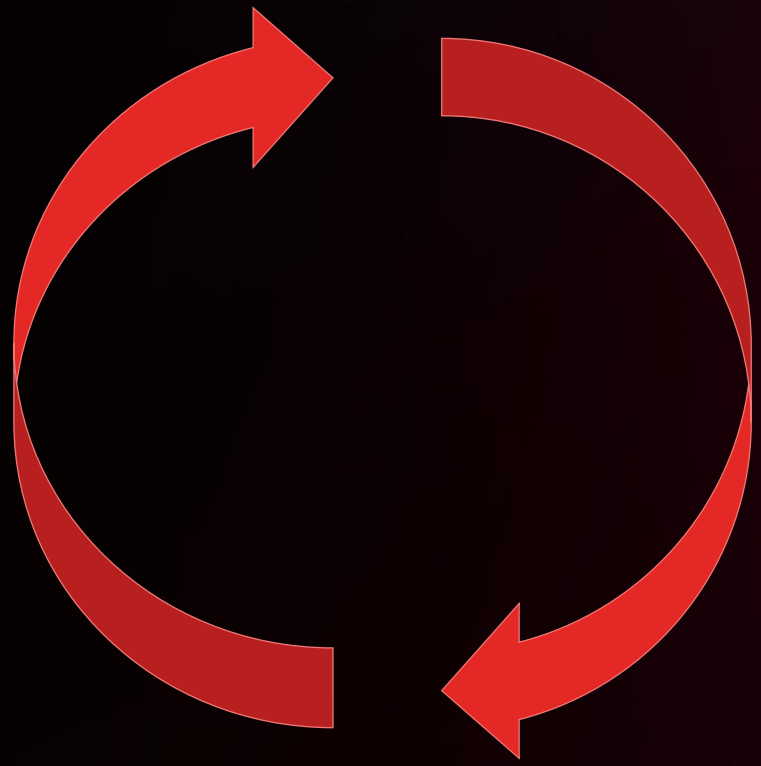


Channeling cathexis*— building up protective factors

*Concentration of emotional energy on an object or idea

Domain experts

What's possible?



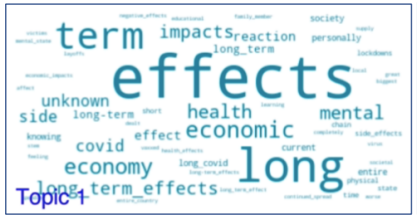
What's needed?

Technologists

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Another application: open-ended survey responses

- Open-ended response from a U.S. nationally representative COVID-19 impact survey, N=1081: *Please tell us more about your concerns or worries about the COVID-19 pandemic, both in the early months of the pandemic and now.*
- Manual selection among models with K = 15, 20, 25, 30
- Curation of a 25-topic model



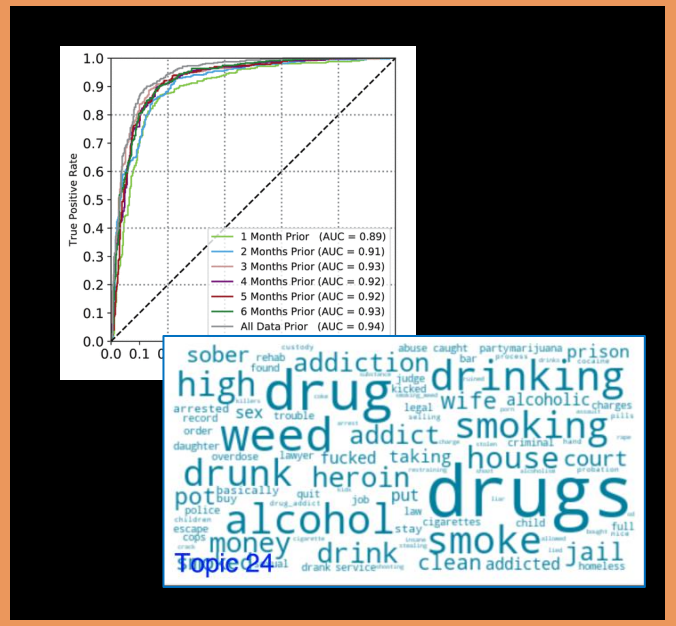
I'm concerned mainly about the economic effects, both long term and short term.
I was just nervous in general about the chain-reaction of effects that would stem ...
I have have and still do worry about both the long term and short term future of ...
Didn't know the long term effects on health and society
I worry about the effects it is going to have in the long term on the people's mental ...
I'm afraid of the long and short term economic and mental health effects.
mostly how it will affect my love ones. Each person is a unique case, some are ...
I have been especially worried about the long term effects- mental, physical and ...

Topic	SME1 Label	SME1 Description	SME2 Label	SME2 Description
1	Societal effects	effects of the pandemic on economy, health and society, particularly in the long term	How do you worry about short and long-term impacts of COVID	Impact of COVID

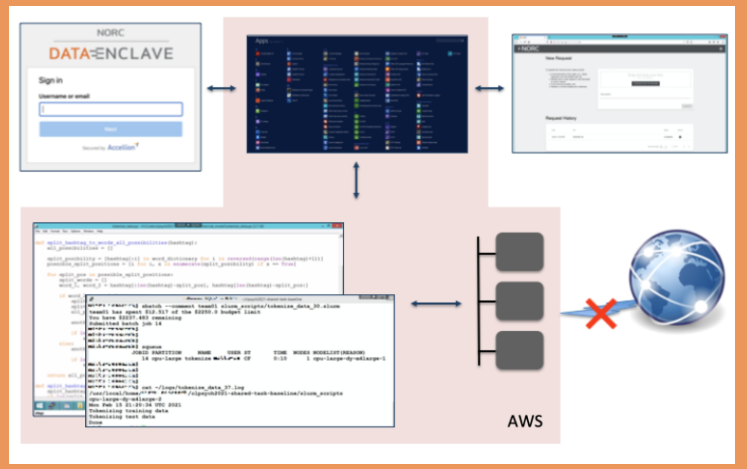
Consensus Label	Consensus Description
Impact of COVID	Short and long-term effects on economy, health, and society (mostly negative)

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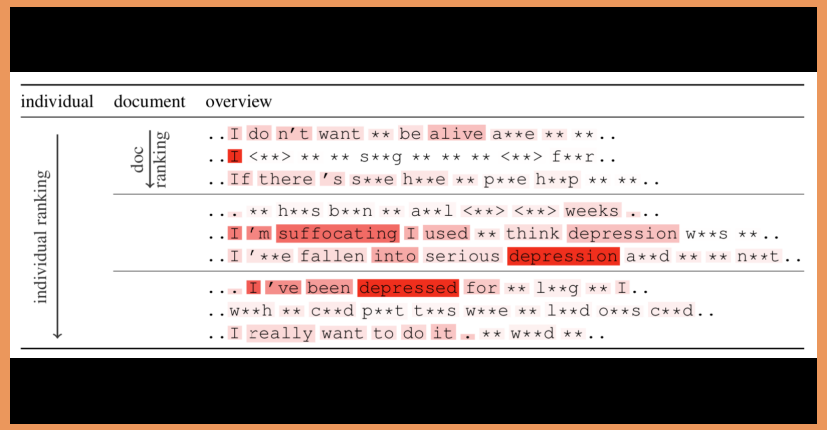
Takeaways



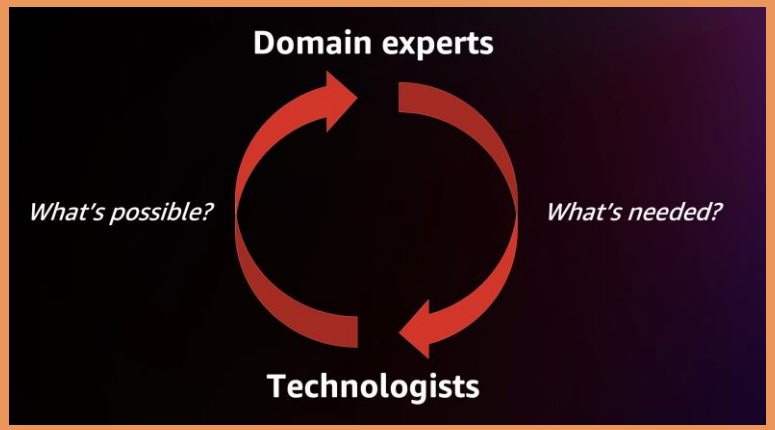
Language contains crucial signals



Enclaves enable sharing sensitive data



We need prioritization,
not just classification



Technology alone is not enough

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Thank you!

Collaborators

- Rebecca Resnik, Pranav Goel, Alexander Hoyle, Rupak Sarkar, Josh Hagedorn, Maeve Gearing, Carol Bruce, April Foreman, Michelle Kuchuk, Katherine Musacchio Schaefer, Beau Pinkham, Jonathan Singer, Sean Macavaney, Anjali Mittu, Glen Coppersmith, Jeff Leintz, Han-Chin Shing, Douglas W. Oard, Suraj Nair, Meir Friedenberg, Hal Daumé III, Igor Galynker, William Armstrong, Leonardo Claudino, Thang Nguyen, Viet-An Nguyen, Jordan Boyd-Graber, Grace Kennedy, Austin Gallyer, Jonathan Singer

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Robust Magnetic Resonance Imaging with Deep Learning

Jon Tamir (he/him)

Assistant Professor, Chandra Family Department of Electrical and Computer Engineering
The University of Texas at Austin

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Topics for today

1. Brief overview of magnetic resonance imaging (MRI) reconstruction
2. Speeding up MRI with deep learning



A Jalal, M Arvinte, G Daras, E Price, AG Dimakis, JI Tamir
Robust Compressed Sensing MRI with Deep Generative Priors
NeurIPS 2021
https://arxiv.org/abs/2108.01368



B Levac, A Jalal, JI Tamir
Accelerated Motion Correction for MRI using Score-Based Generative Models
Arxiv preprint: arXiv:2211.00199
https://arxiv.org/abs/2211.00199

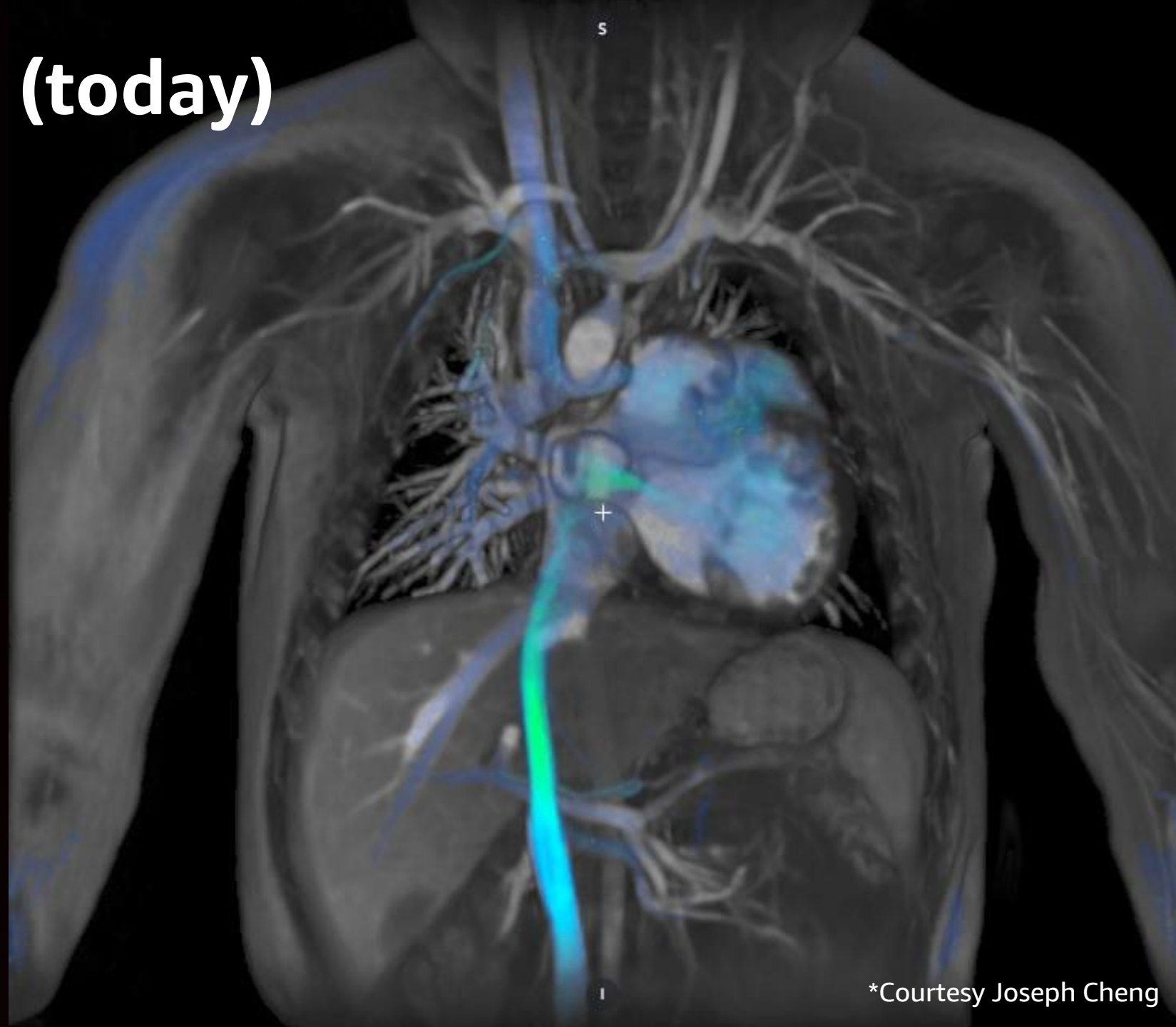
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Medical imaging (today)

Magnetic resonance imaging (MRI)

12 month male (114 bpm)
Scan time: 11:05 min; Total acceleration: 15.0
Resolution: 0.9 x 0.9 x 1.4 mm^3
VENC: (150, 150, 150) cm/s
Contrast: ferumoxytol

Generated using Arterys (San Francisco, CA)



*Courtesy Joseph Cheng

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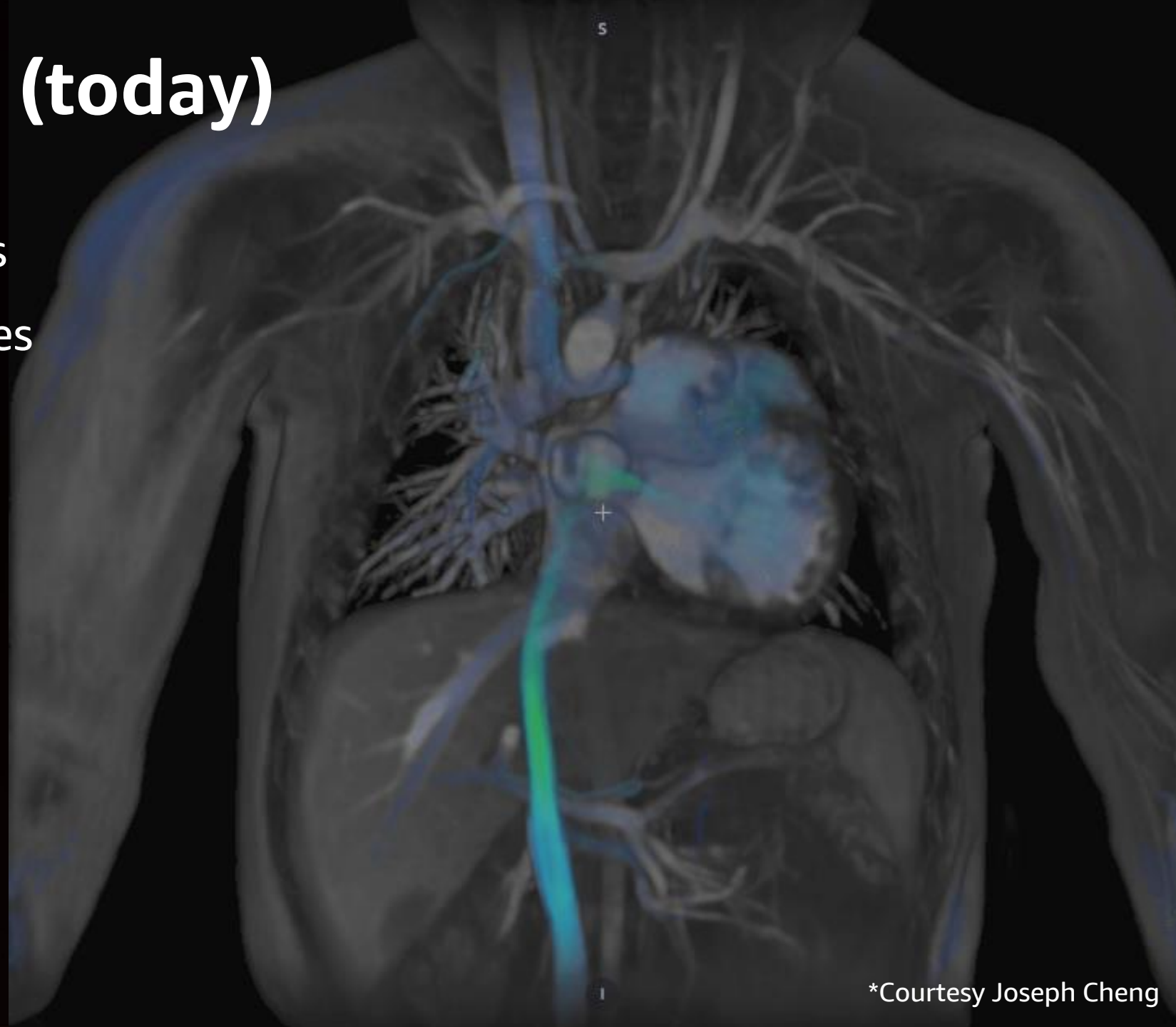
Medical imaging (today)

Rapid and accurate diagnosis

Reduced exploratory surgeries

Better treatment outcomes

Reduced healthcare costs



*Courtesy Joseph Cheng

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Open challenges

Fast imaging

MRI scans orders of magnitude slower compared to computed tomography

Safe imaging

MRI often requires anesthesia for kids

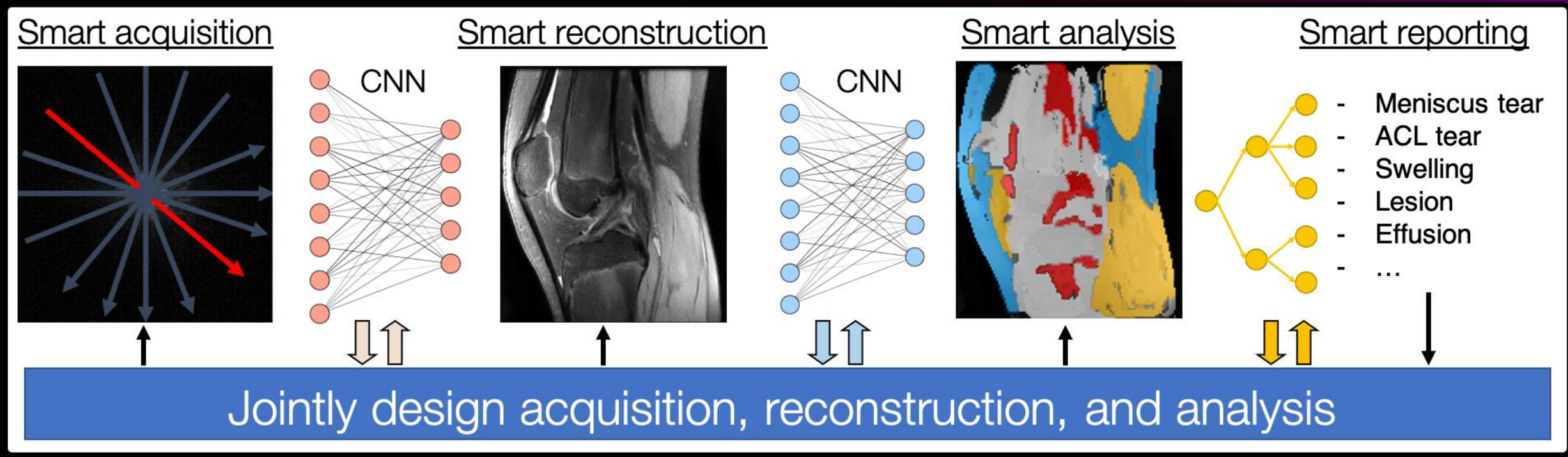
Affordable imaging

MRI is expensive and often inaccessible

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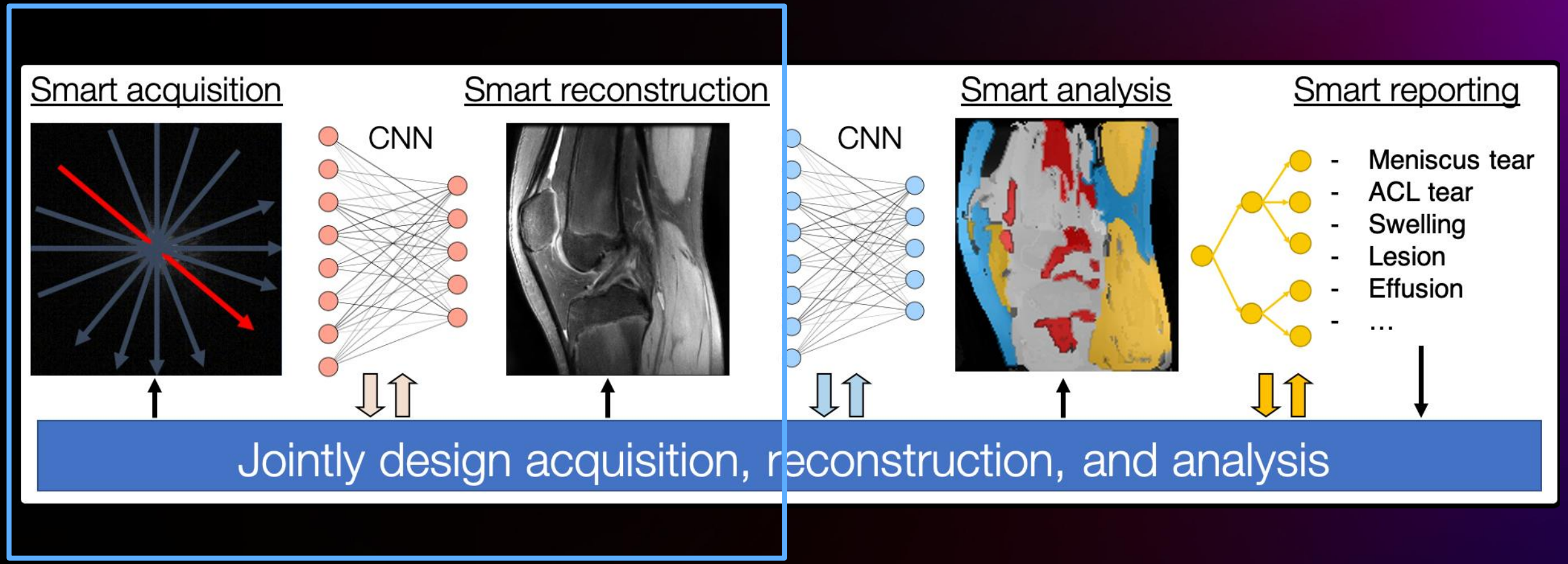
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Computational MRI



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Computational MRI



Focus of this work

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MRI: Frequency domain formulation

Signal is the Fourier transform of the image

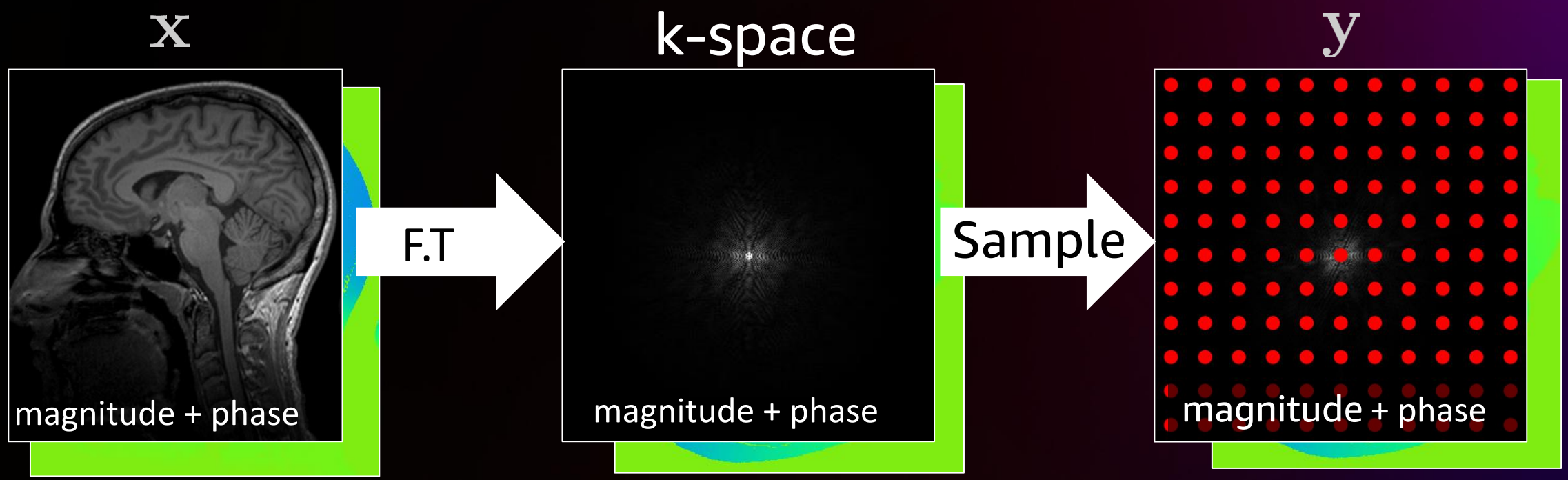
$$\mathbf{y} = \mathbf{A}\mathbf{x} + \text{noise}$$

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MRI: Frequency domain formulation

Signal is the Fourier transform of the image

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \text{noise}$$

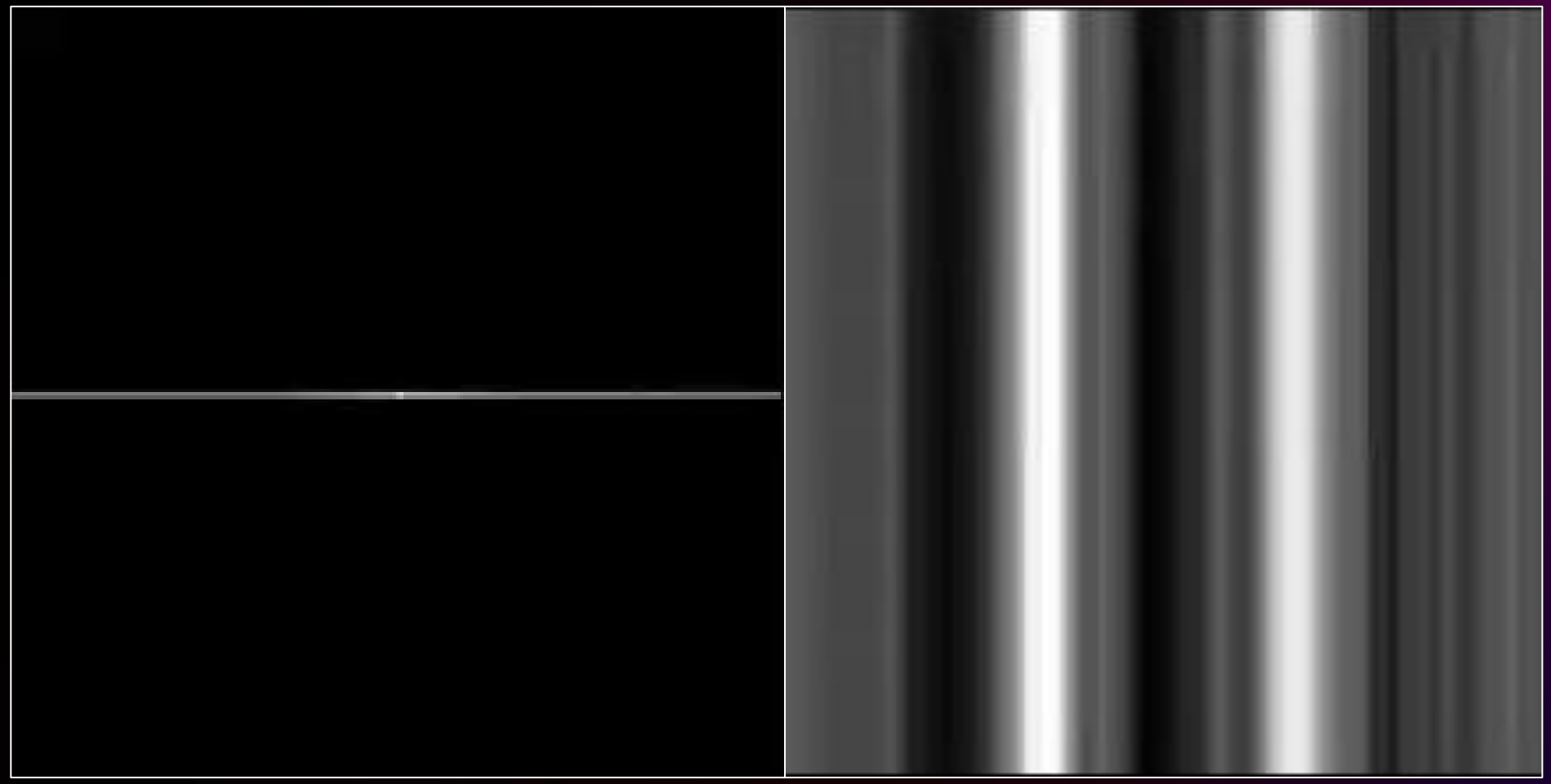


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MRI: Frequency domain formulation

k-space domain

image



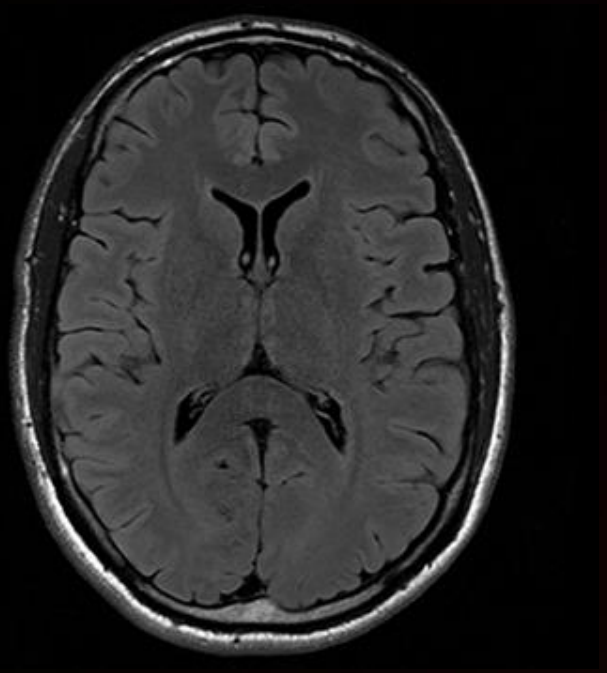
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Collecting (less) data

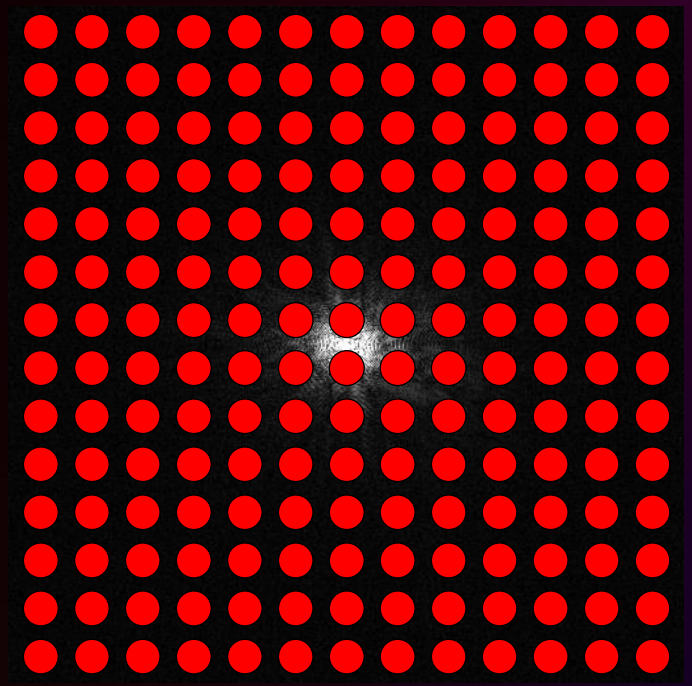
Scan time is proportional to number of measurements

- Collect less data → scan faster!
- Under-sampling causes artifacts

image space



k-space





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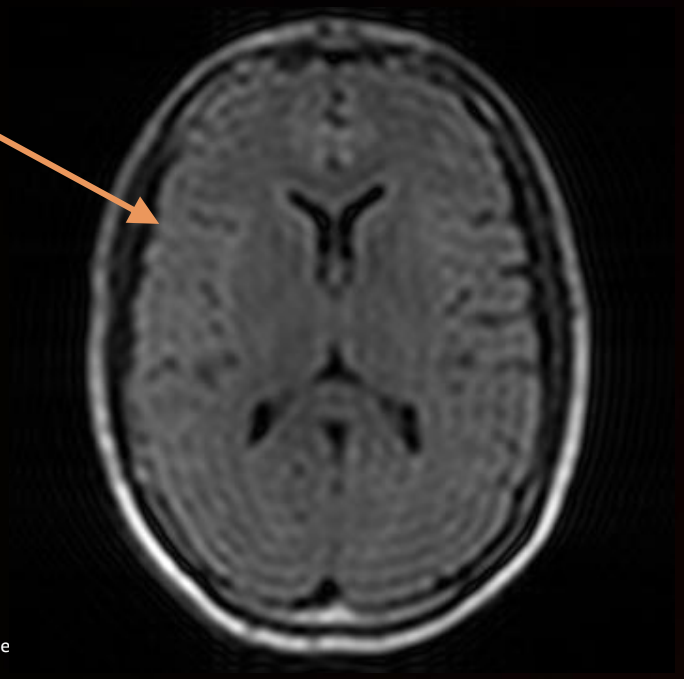
Collecting (less) data

Scan time is proportional to number of measurements

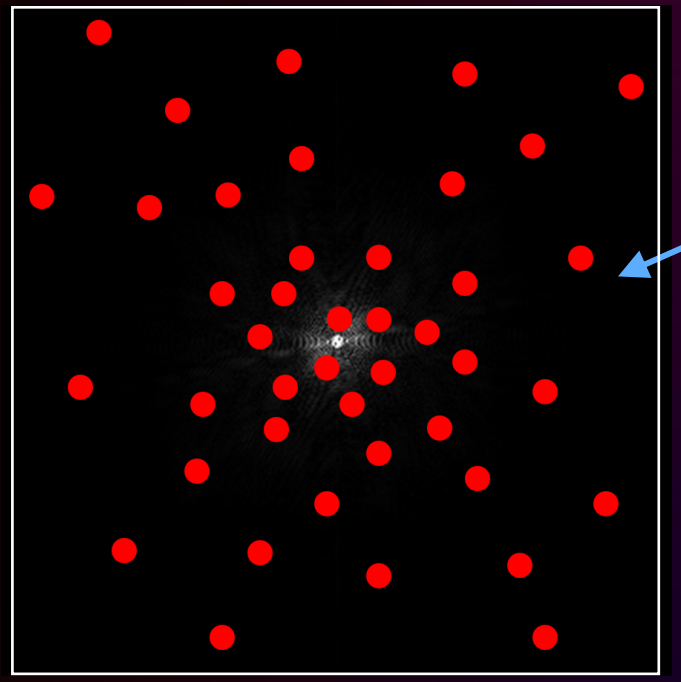
- Collect less data → scan faster!
- Under-sampling causes artifacts

image space

Artifacts



k-space



3x faster scan

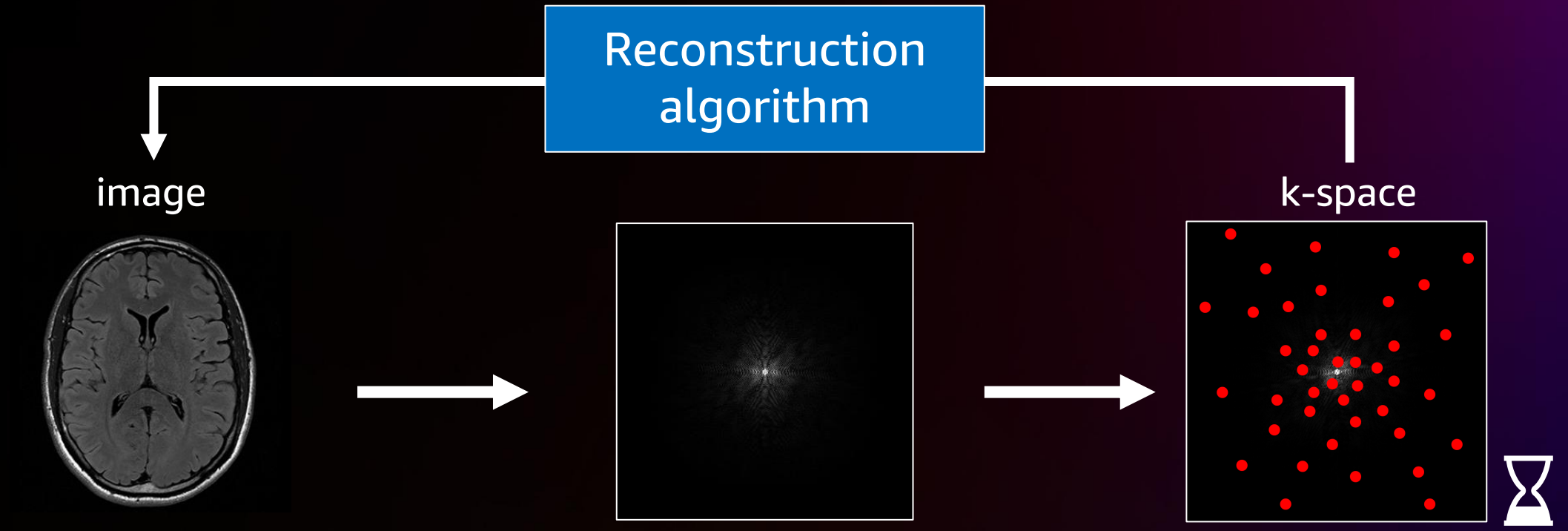


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Image reconstruction as an inverse problem

Goal: Recover the image from limited measurements

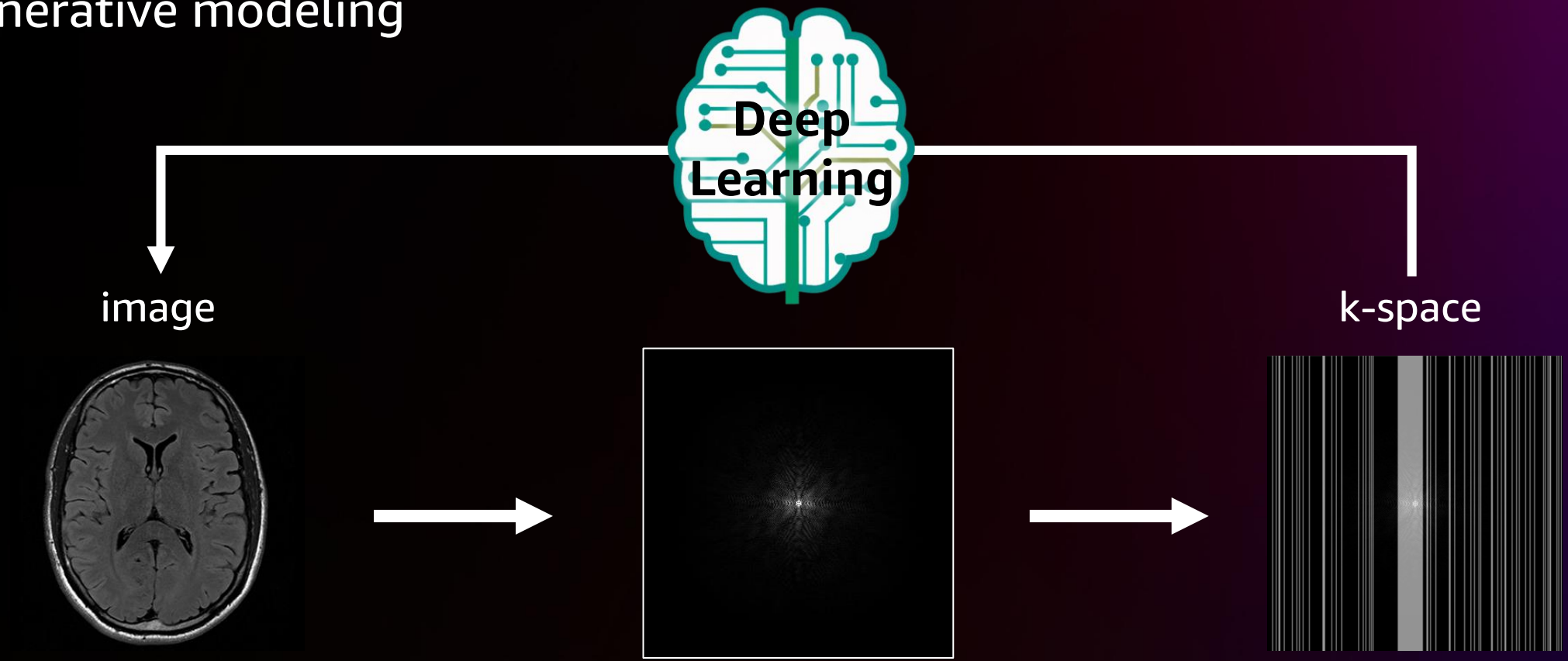
Ill-posed –incorporate prior knowledge



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Deep learning reconstruction for MRI

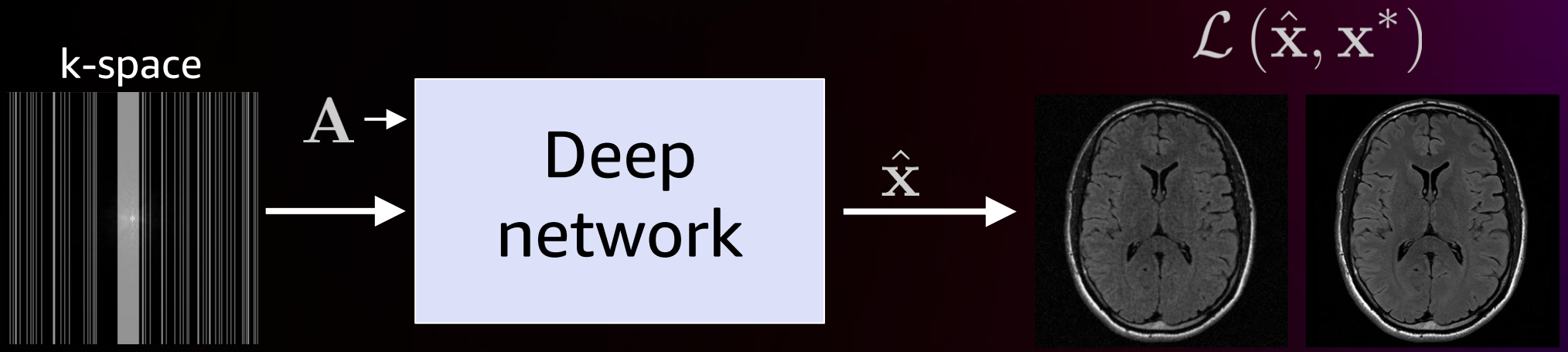
1. End-to-end supervised training
2. Generative modeling



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End-to-end supervised training

Goal: Learn to invert the forward model with deep networks



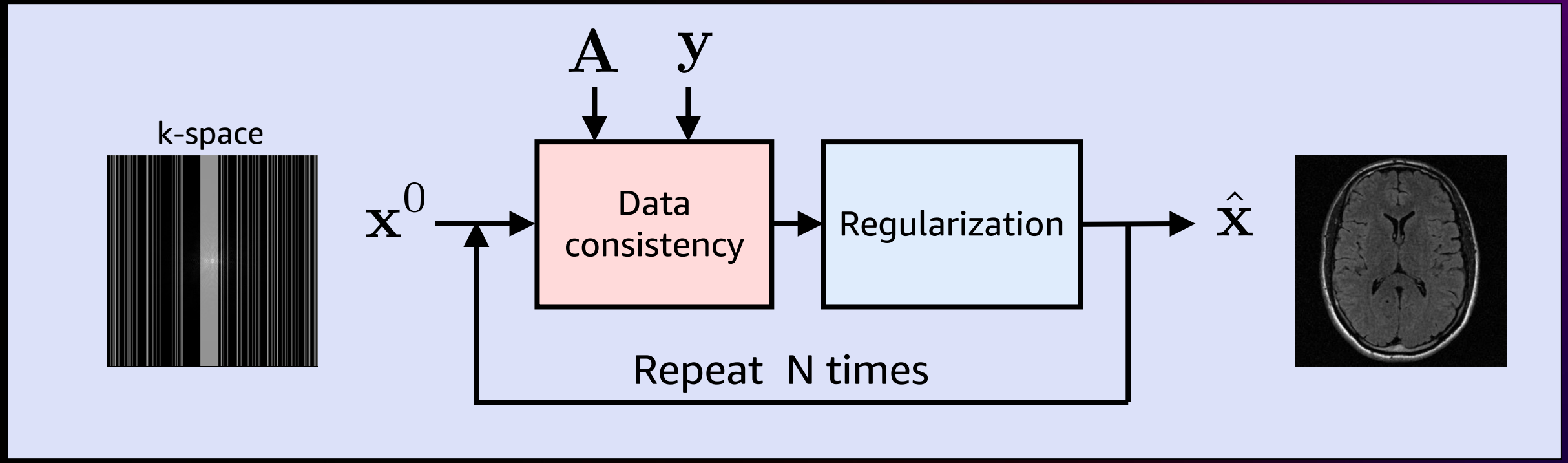
J Schlemper et al., IPMI, 2017. K Hammernik et al., MRM 2017. HK Aggarwal et al., IEEE TMI 2019. A Sriram et al., MICCAI 2020. M Arvinte et al., MICCAI 2021.

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End-to-end supervised training

Iterative reconstruction algorithm

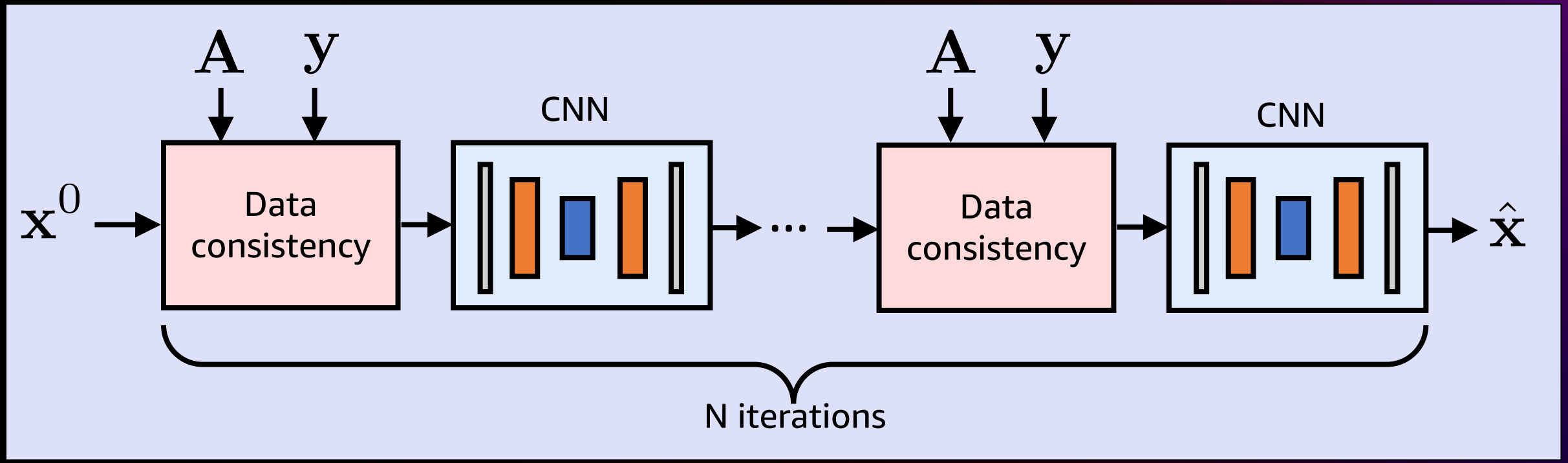


J Schlemper et al., IPMI, 2017. K Hammernik et al., MRM 2017. HK Aggarwal et al., IEEE TMI 2019. A Sriram et al., MICCAI 2020. M Arvinte et al., MICCAI 2021.

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End-to-end supervised training

Unrolled reconstruction algorithm



J Schlemper et al., IPMI, 2017. K Hammernik et al., MRM 2017. HK Aggarwal et al., IEEE TMI 2019. A Sriram et al., MICCAI 2020. M Arvinte et al., MICCAI 2021.

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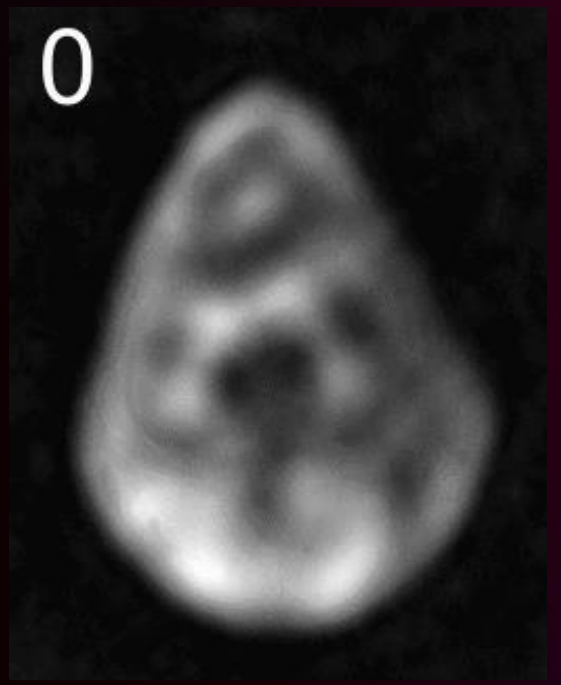
End-to-end supervised training

Pseudocode

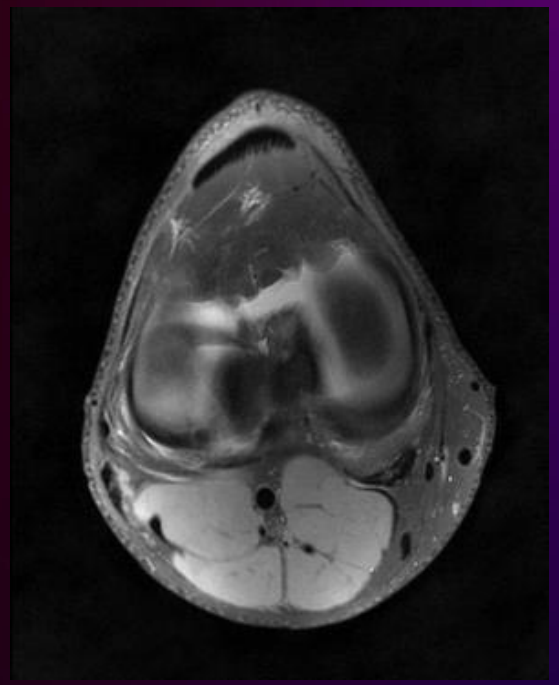
```
deep_net = MyCNN(...)
data_con = DataConsistency(...)
...
x_hat = zeros(...) # initialize x
for iter in range(max_iter):
  x_hat = data_con(x_hat, y, A)
  x_hat = deep_net(x_hat)

loss = MyLoss(x_hat, x_gt)
```

Reconstruction



Ground truth



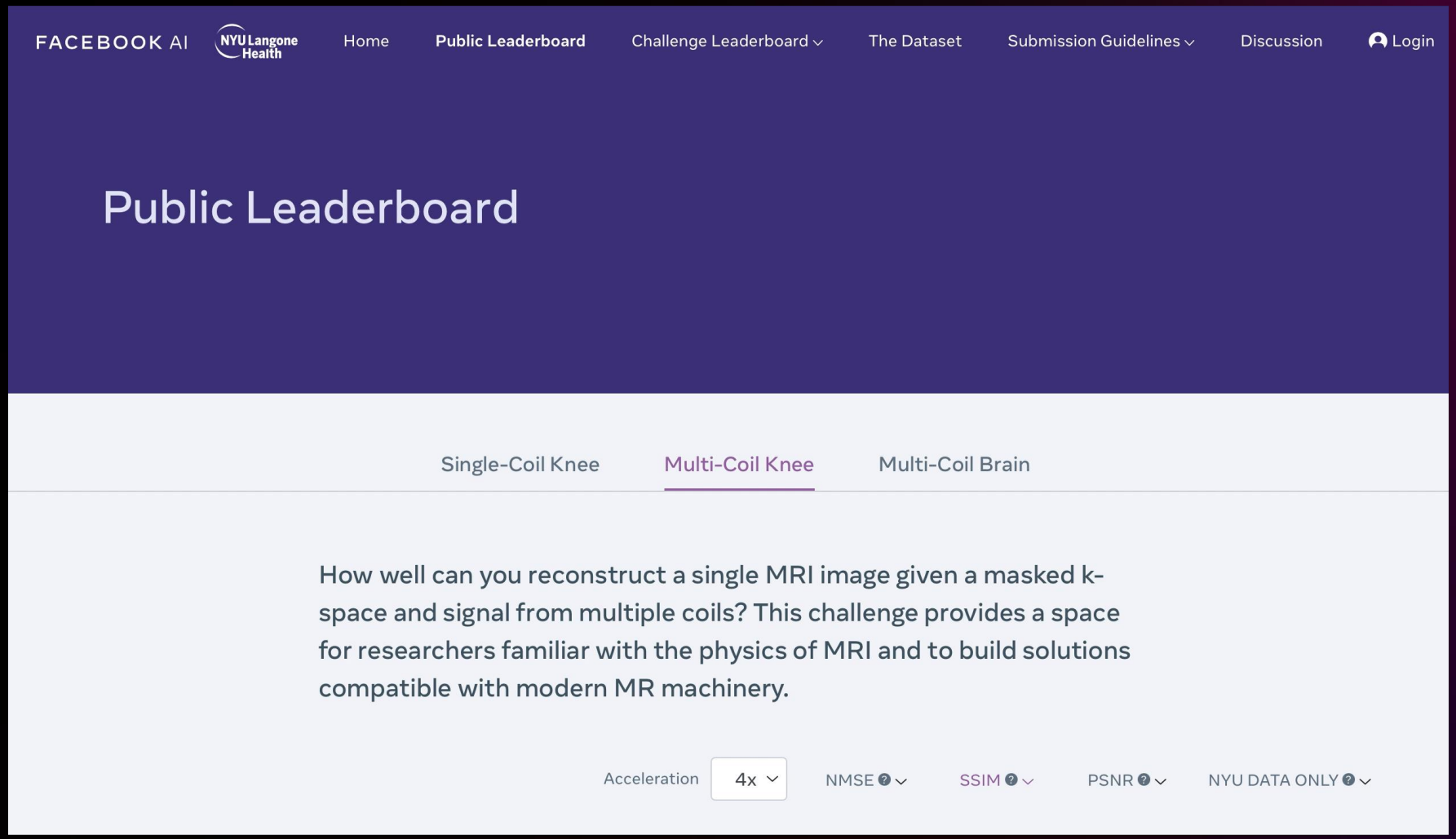
J Schlemper et al., IPMI, 2017. K Hammernik et al., MRM 2017. HK Aggarwal et al., IEEE TMI 2019. A Sriram et al., MICCAI 2020. M Arvinte et al., MICCAI 2021.

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End-to-end supervised training is state of the art*

*for in-distribution testing



fastmri.org

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Drawbacks of end-to-end supervised training

1. Deep network is **coupled** to the measurement process

2. Estimating uncertainty is **challenging**

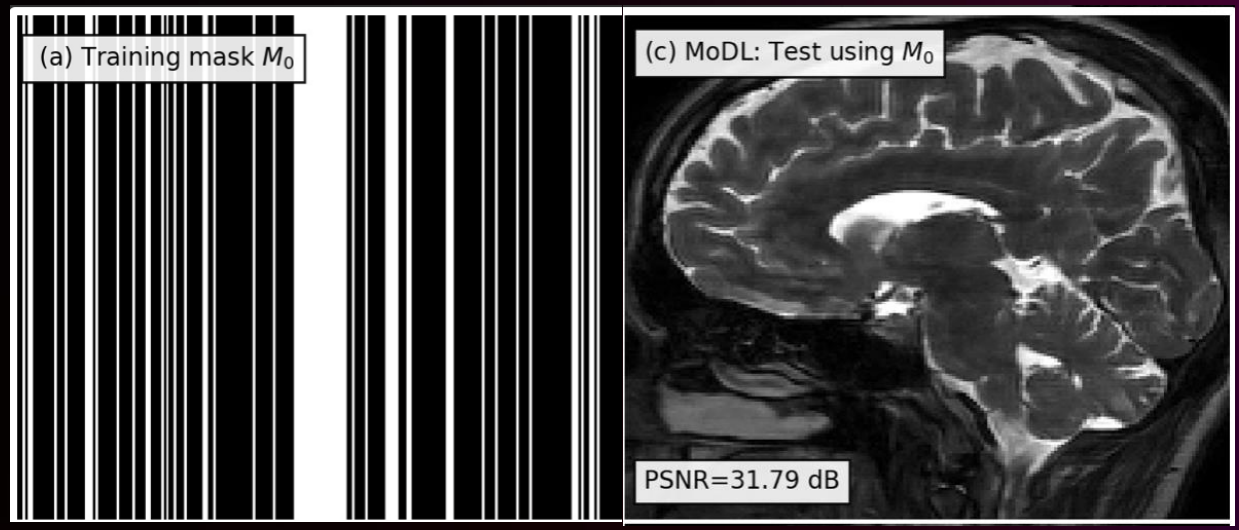
3. Reconstruction is **over-tuned** to a specific anatomy and contrast

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Drawbacks of end-to-end supervised training

1. Deep network is **coupled** to the measurement process



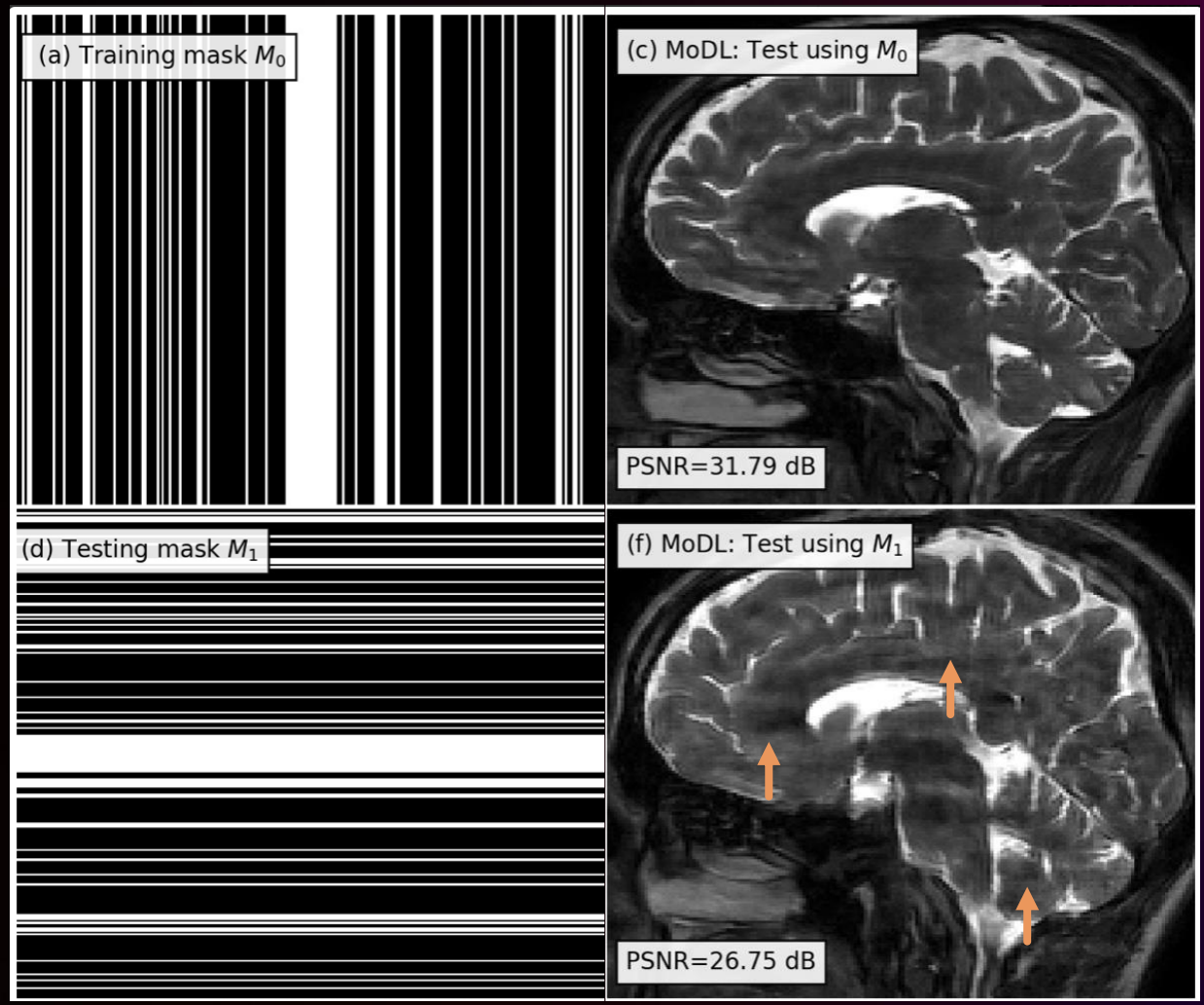
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From HK Aggarwal and M Jacob, ISMRM 2021 #1960

Drawbacks of end-to-end supervised training

1. Deep network is **coupled** to the measurement process

Performance degrades when training and testing conditions differ



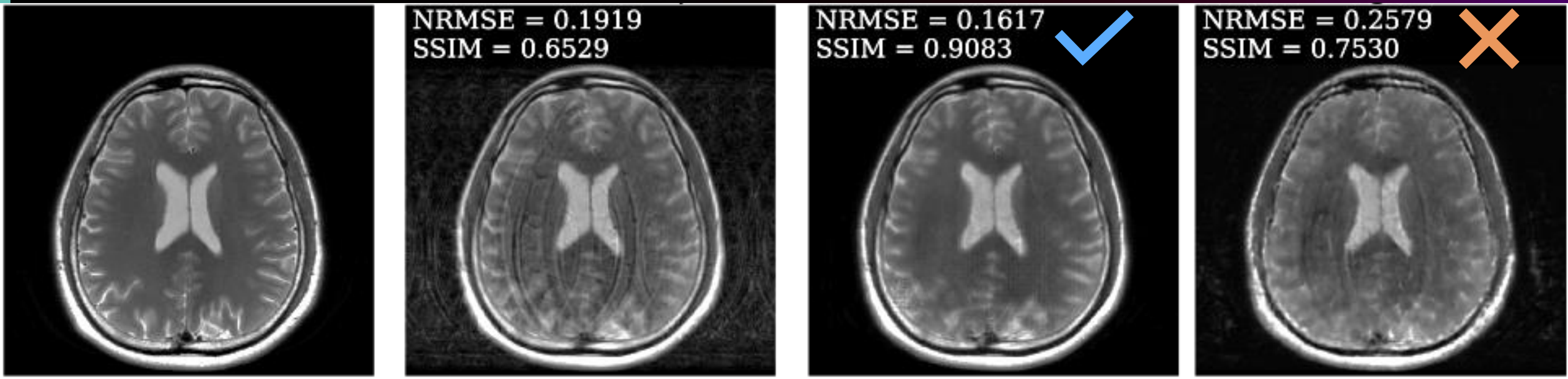
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From HK Aggarwal and M Jacob, ISMRM 2021 #1960

Drawbacks of end-to-end supervised training

1. Deep network is **coupled** to the measurement process

Ground-truth | Motion-corrupt | Motion-corrected | Train/test mismatch



In-distribution

Out of distribution

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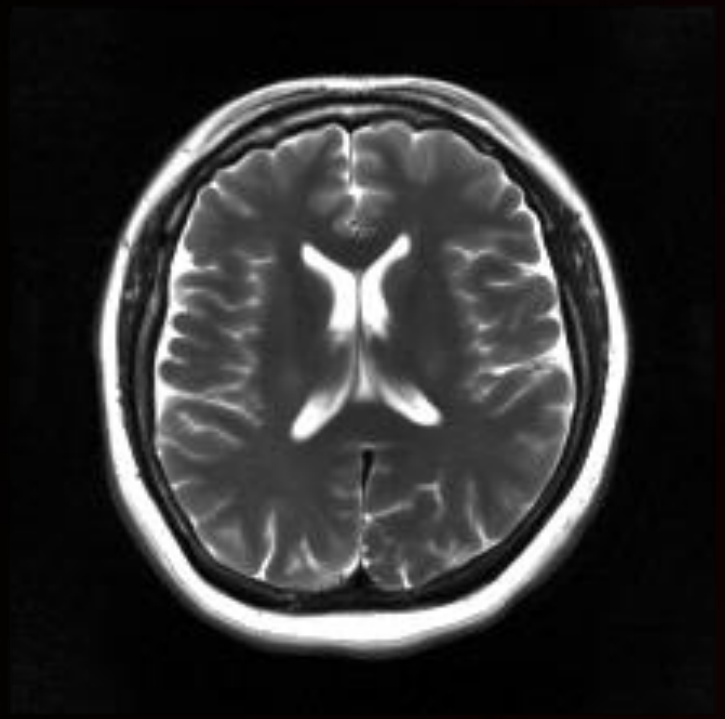
B Levac, S Kumar, S Kardonik, JI Tamir, MICCAI 2022

Drawbacks of end-to-end supervised training

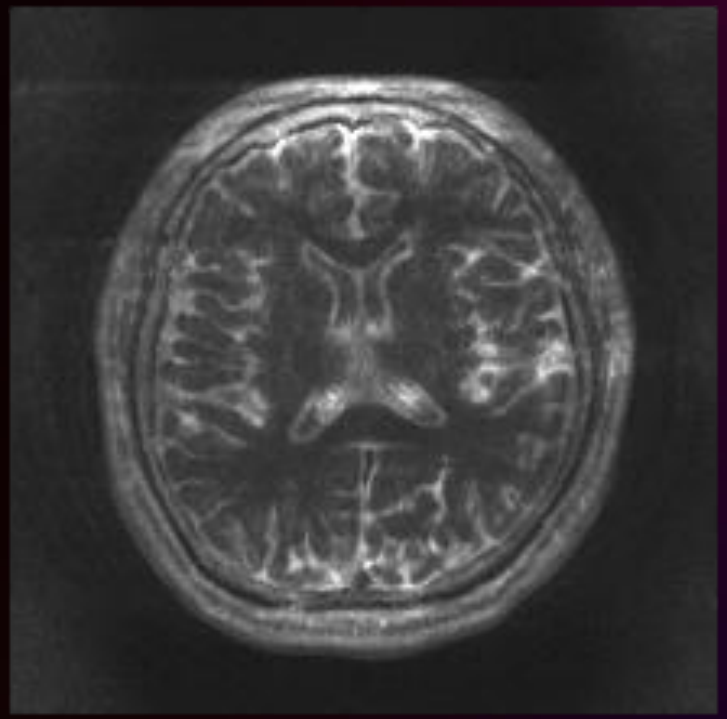
2. Estimating uncertainty is **challenging**

    Requires (i) new architecture, (ii) retraining, (iii) or both

Reconstruction



Uncertainty map



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Back to basics: statistical interpretation

We want to estimate the image from noisy measurements

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \text{noise}$$

Maximum Likelihood: maximize the probability of a specific outcome given a parameter:

$$\max_{\mathbf{x}} p(\mathbf{y}|\mathbf{x})$$

Prior knowledge: probability distribution for the image: $p(\mathbf{x})$

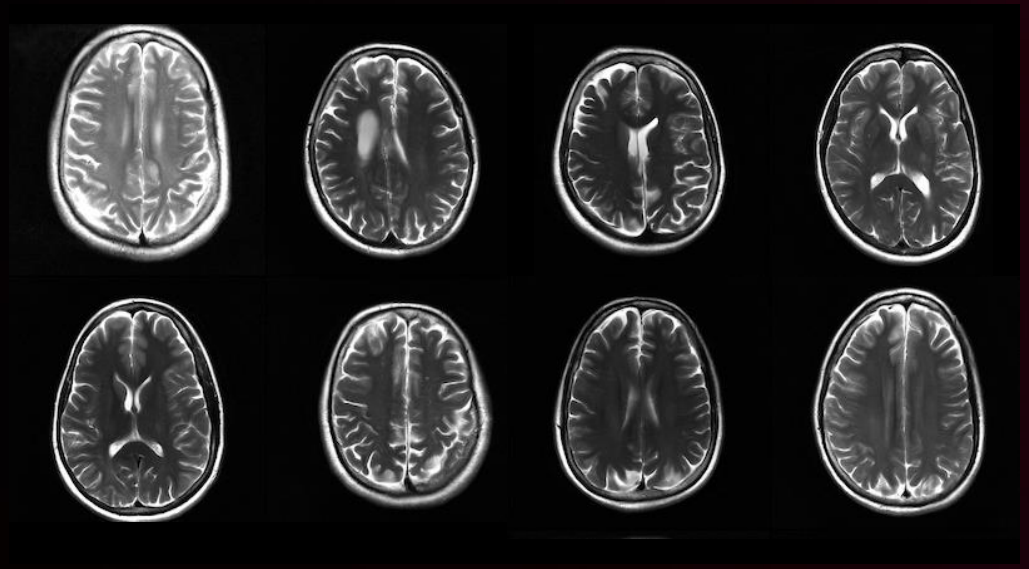
Combining the two: **posterior distribution** $p(\mathbf{x}|\mathbf{y})$

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Generative modeling

Goal: Use deep networks to learn the prior distribution



Samples from $p(x)$

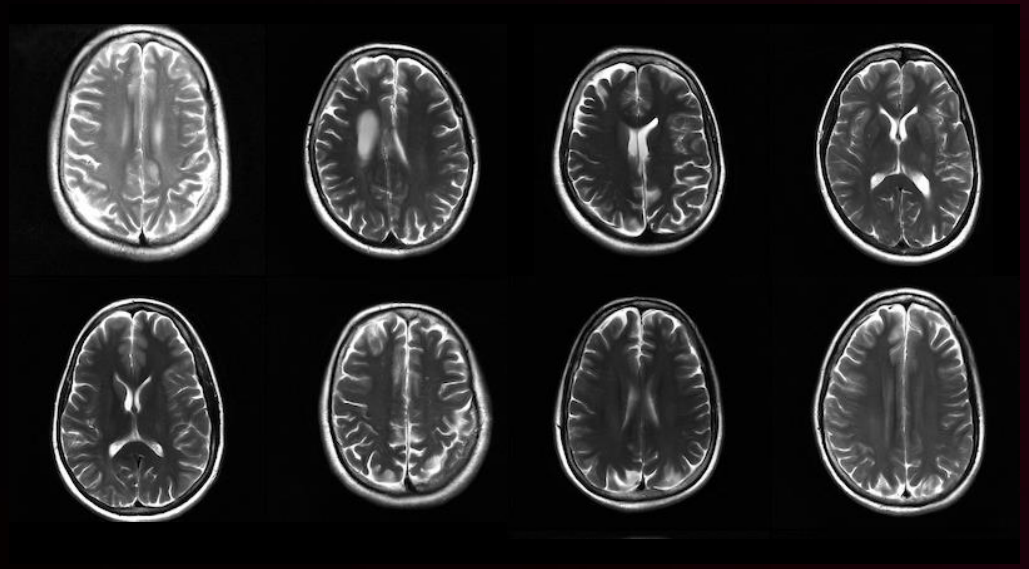
A Bora et al., ICML 2017. Y Song and S Ermon, NeurIPS 2019. P Dhariwal and A Nichol, arXiv preprint, arXiv:2105.05233

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Generative modeling

Goal: Use deep networks to learn the prior distribution



Samples from $p(x)$

Decouple statistical image prior from measurement model

Apply Bayesian principles for reconstruction

A Bora et al., ICML 2017. Y Song and S Ermon, NeurIPS 2019. P Dhariwal and A Nichol, arXiv preprint, arXiv:2105.05233

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Generative models are powerful image generators



T Karras et al., CVPR 2020



Y Song et al., ICLR 2021

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Generative models are powerful image generators





https://thiscatdoesnotexist.com

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y A x^*



Random Gaussian measurements

RGB, $x \geq 0$

"Benchmark" linear inverse problem

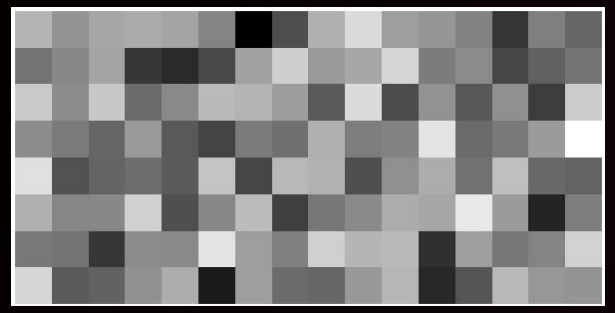
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Source: CelebA-HQ, https://mmlab.ie.cuhk.edu.hk/projects/CelebA.html

y A x^*



=



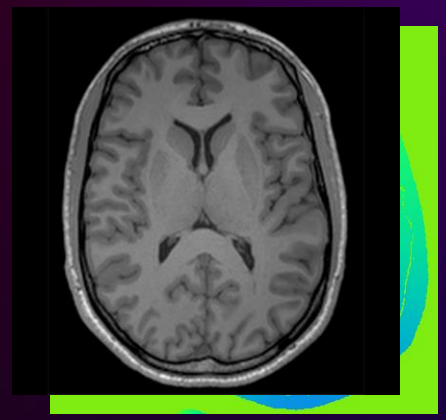
Random Gaussian measurements



RGB, $x \geq 0$

"Benchmark" linear inverse problem

MRI



Complex-valued

aws

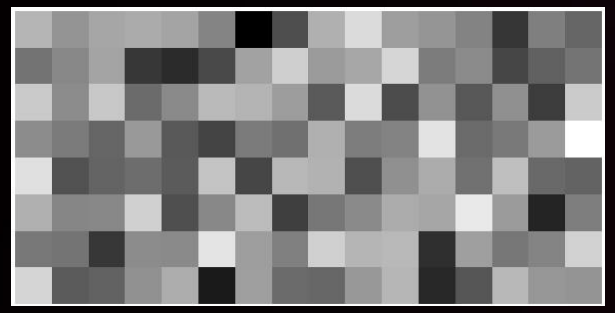
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Source: CelebA-HQ, https://mmlab.ie.cuhk.edu.hk/projects/CelebA.html

y A x^*



=

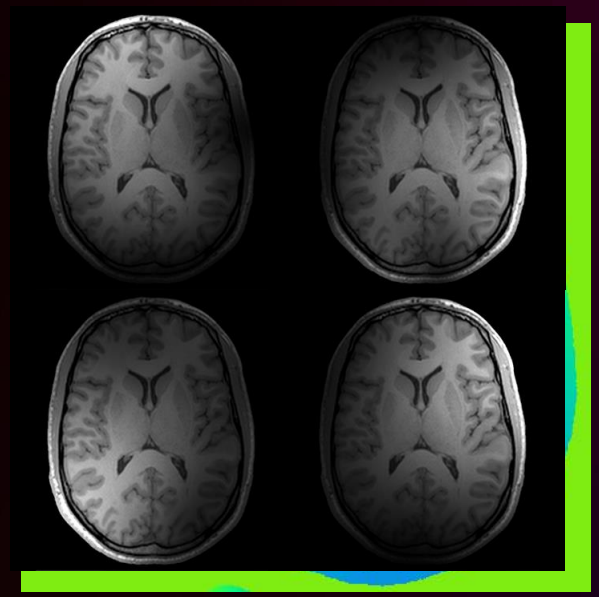


Random Gaussian measurements



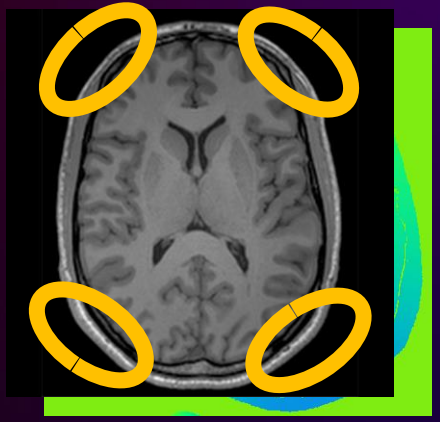
RGB, $x \geq 0$

"Benchmark" linear inverse problem



Multiple receive coils

MRI



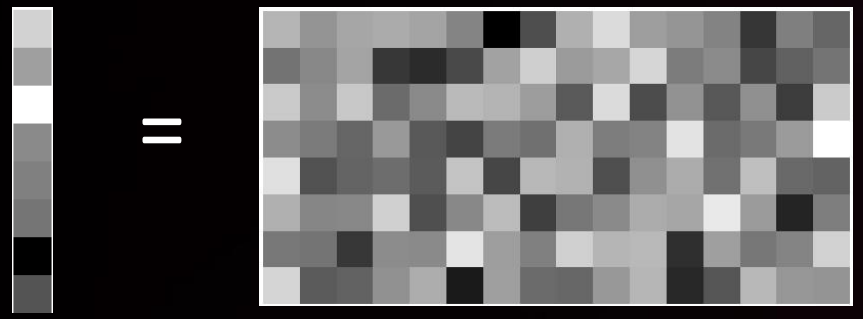
Complex-valued

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Source: CelebA-HQ, https://mmlab.ie.cuhk.edu.hk/projects/CelebA.html

y A x^*



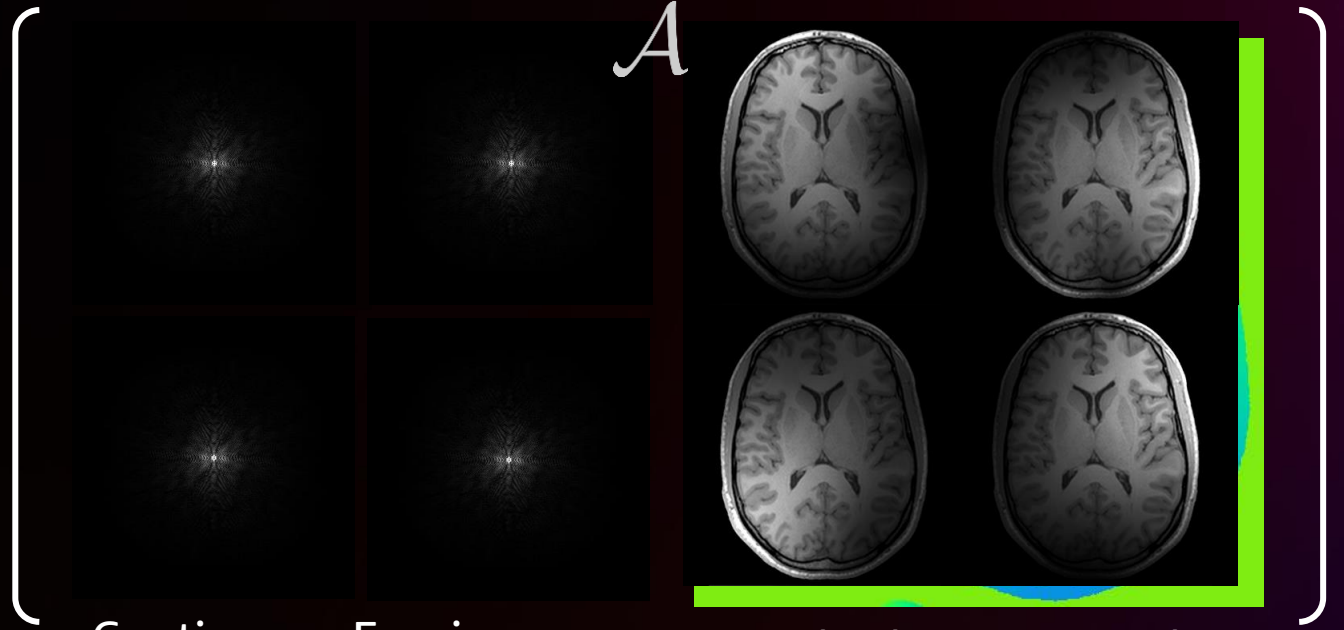
Random Gaussian measurements



RGB, $x \geq 0$

"Benchmark" linear inverse problem

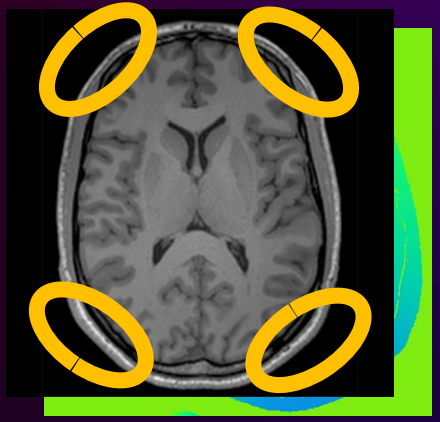
$\mathcal{A}$



Continuous Fourier space

Multiple receive coils

MRI



Complex-valued

aws

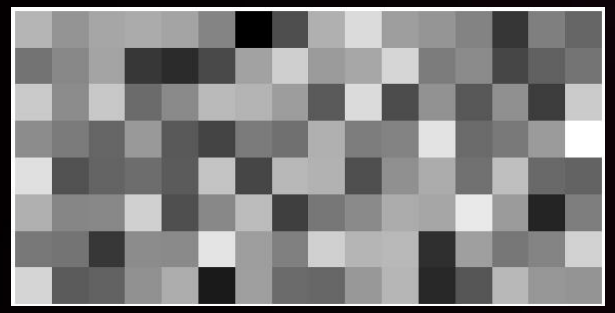
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Source: CelebA-HQ, https://mmlab.ie.cuhk.edu.hk/projects/CelebA.html

y A x^*



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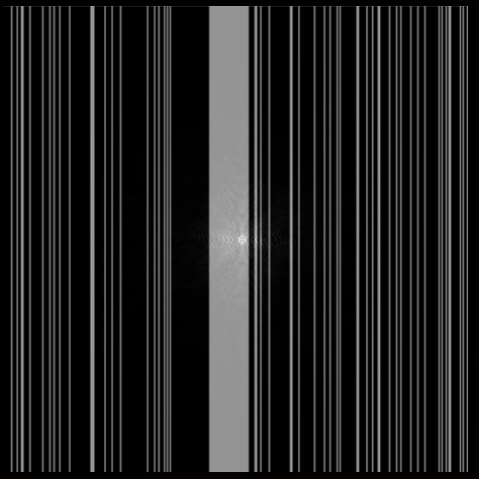
Random Gaussian measurements



RGB, $x \geq 0$

"Benchmark" linear inverse problem

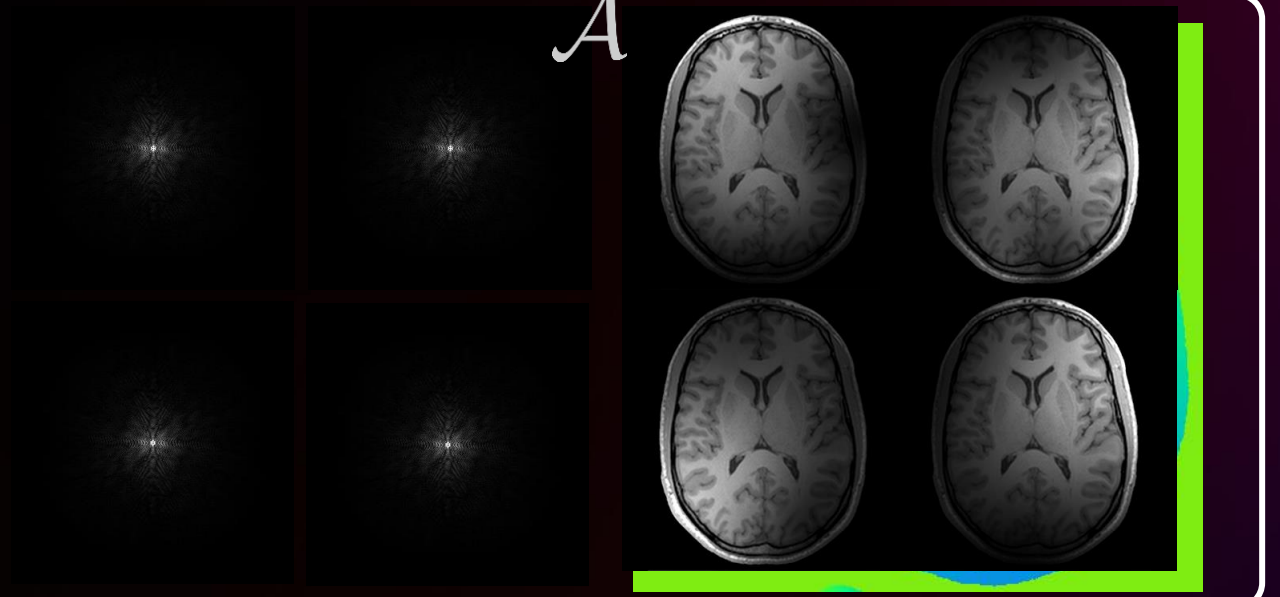
y (x4)



Random 1D sampling

=

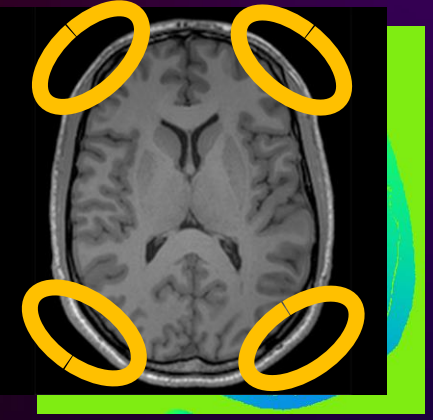
$\mathcal{A}$



Continuous Fourier space

Multiple receive coils

MRI



Complex-valued

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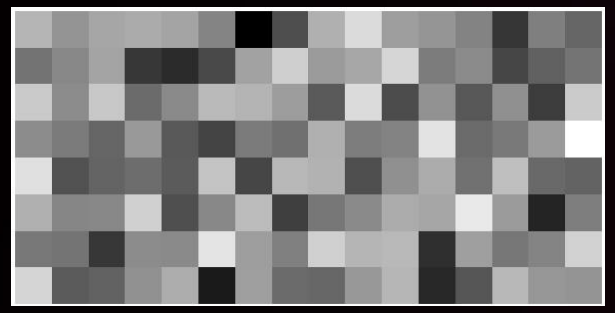
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Source: CelebA-HQ, https://mmlab.ie.cuhk.edu.hk/projects/CelebA.html

y A x^*



=



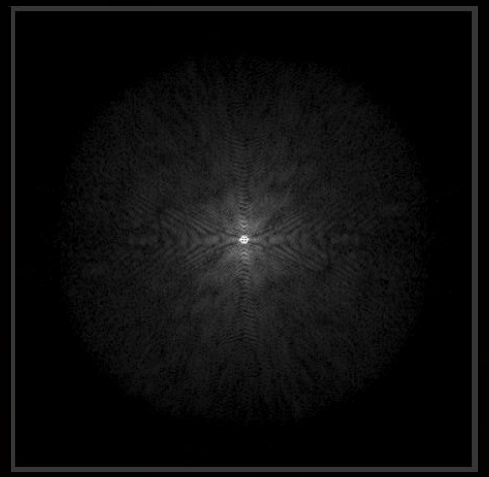
Random Gaussian measurements



RGB, $x \geq 0$

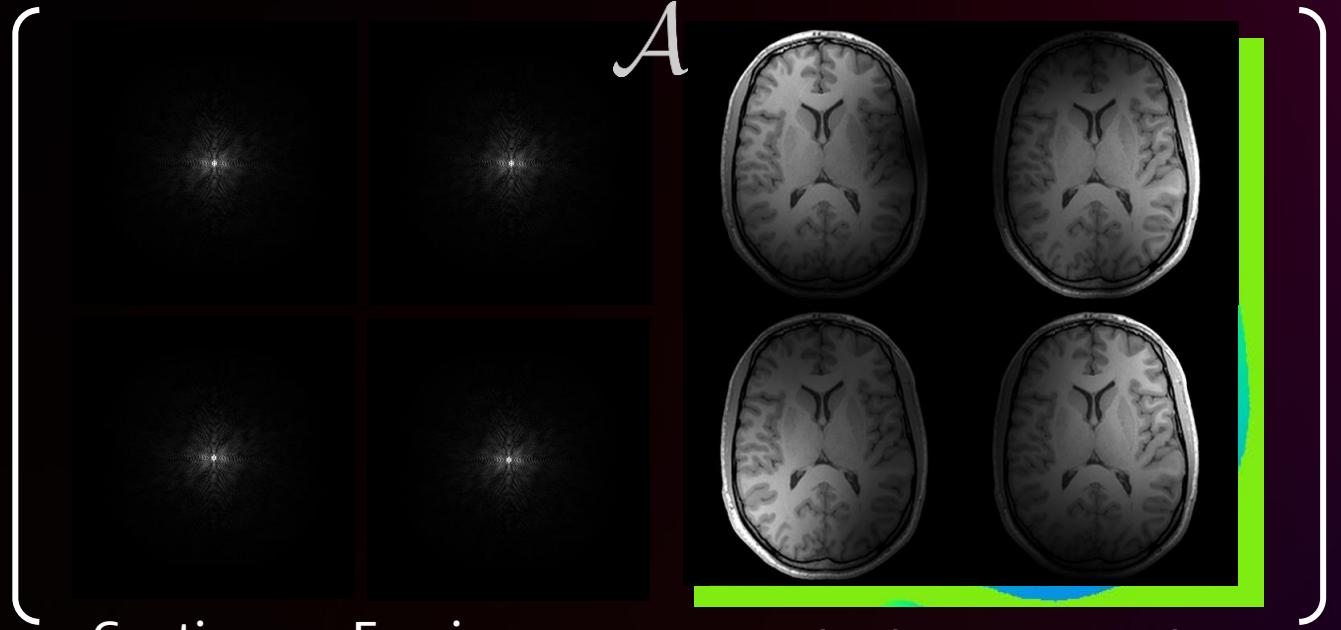
"Benchmark" linear inverse problem

y (x4)



Random 1D sampling

=

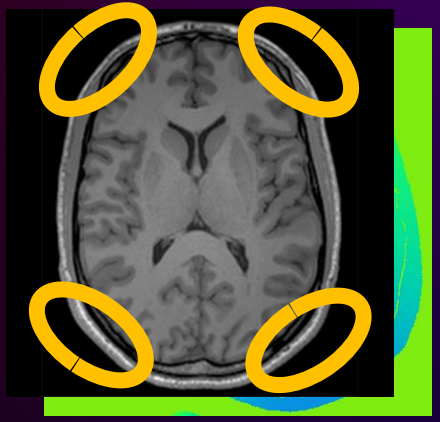


$\mathcal{A}$

Continuous Fourier space

Multiple receive coils

MRI



Complex-valued

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Source: CelebA-HQ, https://mmlab.ie.cuhk.edu.hk/projects/CelebA.html

Reference



Reconstruction



“Superior visual reconstructions”

G Daras, et al., ICML 2021

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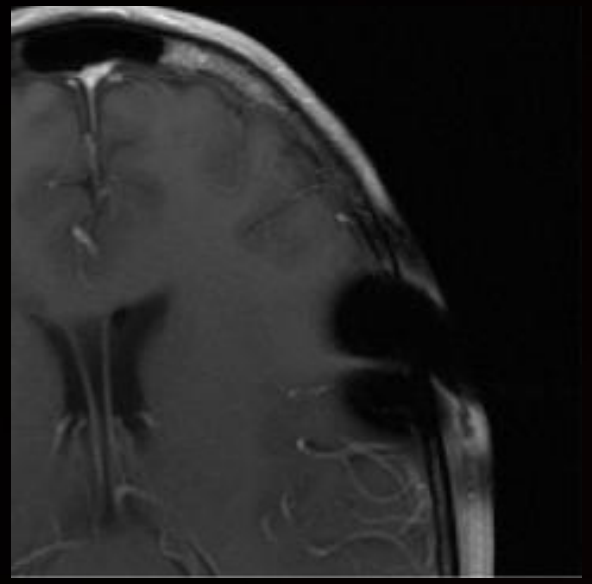
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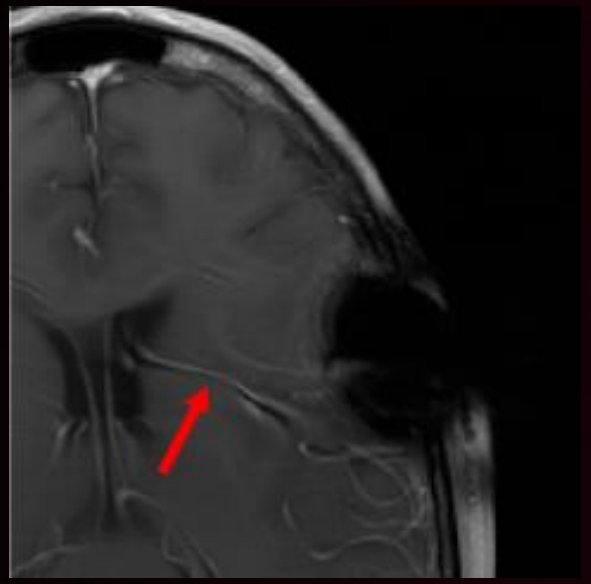
Reference

Reconstruction









"Superior visual reconstructions"

G Daras, et al., ICML 2021

"generated a false vessel, possibly related to susceptibilities introduced by surgical staples "

Muckley et al., IEEE TMI, 2021

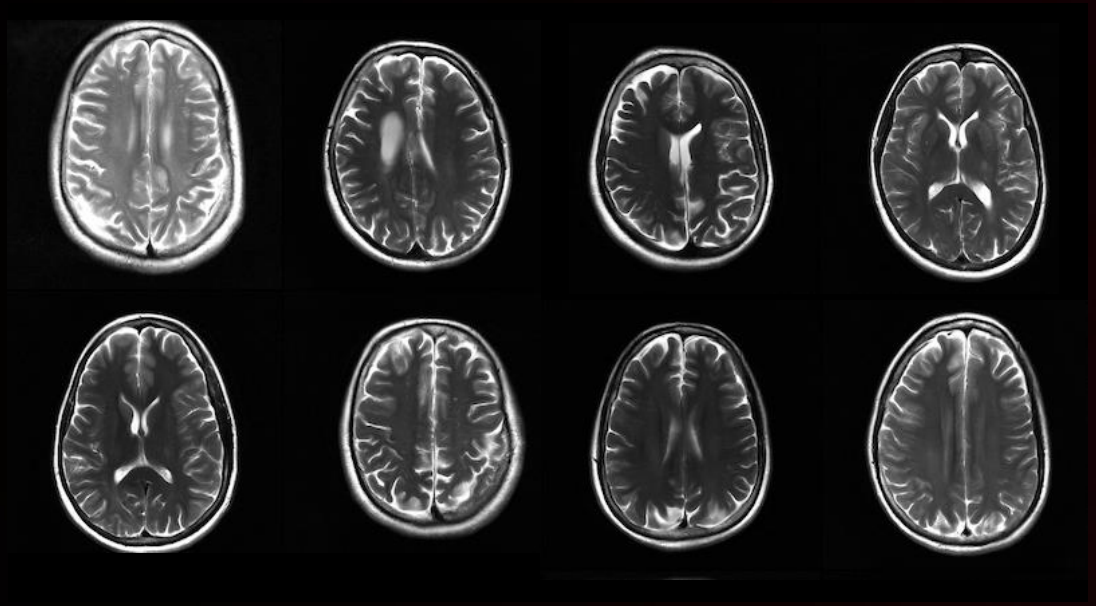
Source: CelebA-HQ, https://mmlab.ie.cuhk.edu.hk/projects/CelebA.html

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Our work: Robust MRI with deep generative priors

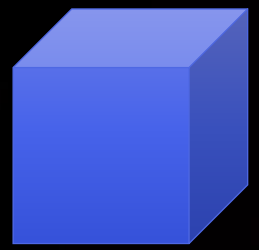
- Theoretical evidence for robustness of posterior sampling
- Competitive with end-to-end methods **in-distribution**
- Robust to anatomy and sampling shifts
- Provides notion of uncertainty



A Jalal*, M Arvinte*, et al., NeurIPS 2021
H Chung, JC Ye, Medical Imaging Analysis, 2022
G Luo, M Heide, M Uecker, arXiv:2202.01479

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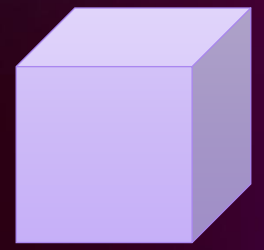
Score-based generative models



x
(image)

Deep network
$s_w(x)$

$\nabla \log p_X(x)$



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Y Song, S Ermon, NeurIPS 2019. D Prafulla, A Nichol, NeurIPS 2021.

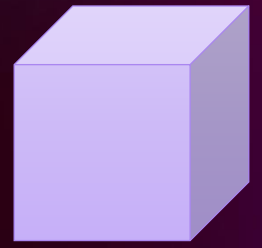
Score-based generative models

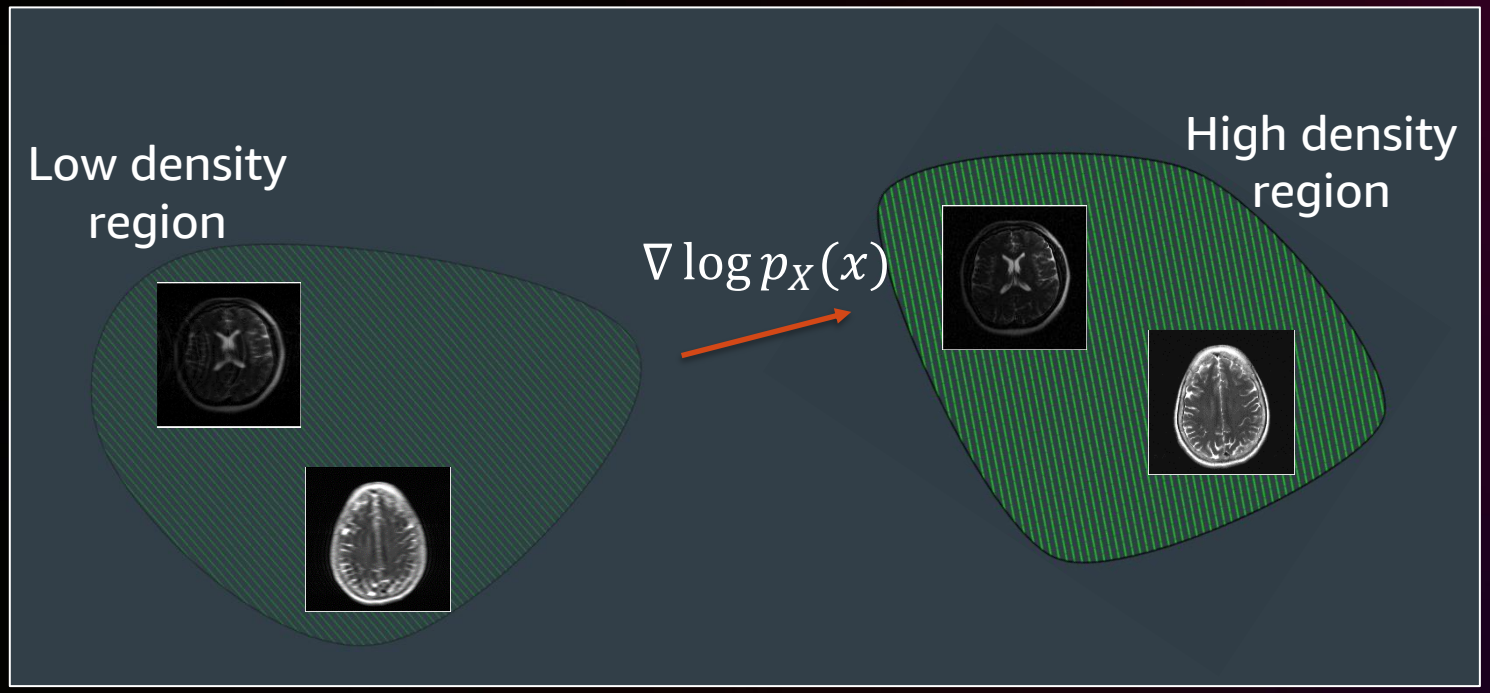


x
(image)

Deep network
$s_w(x)$

$\nabla \log p_X(x)$





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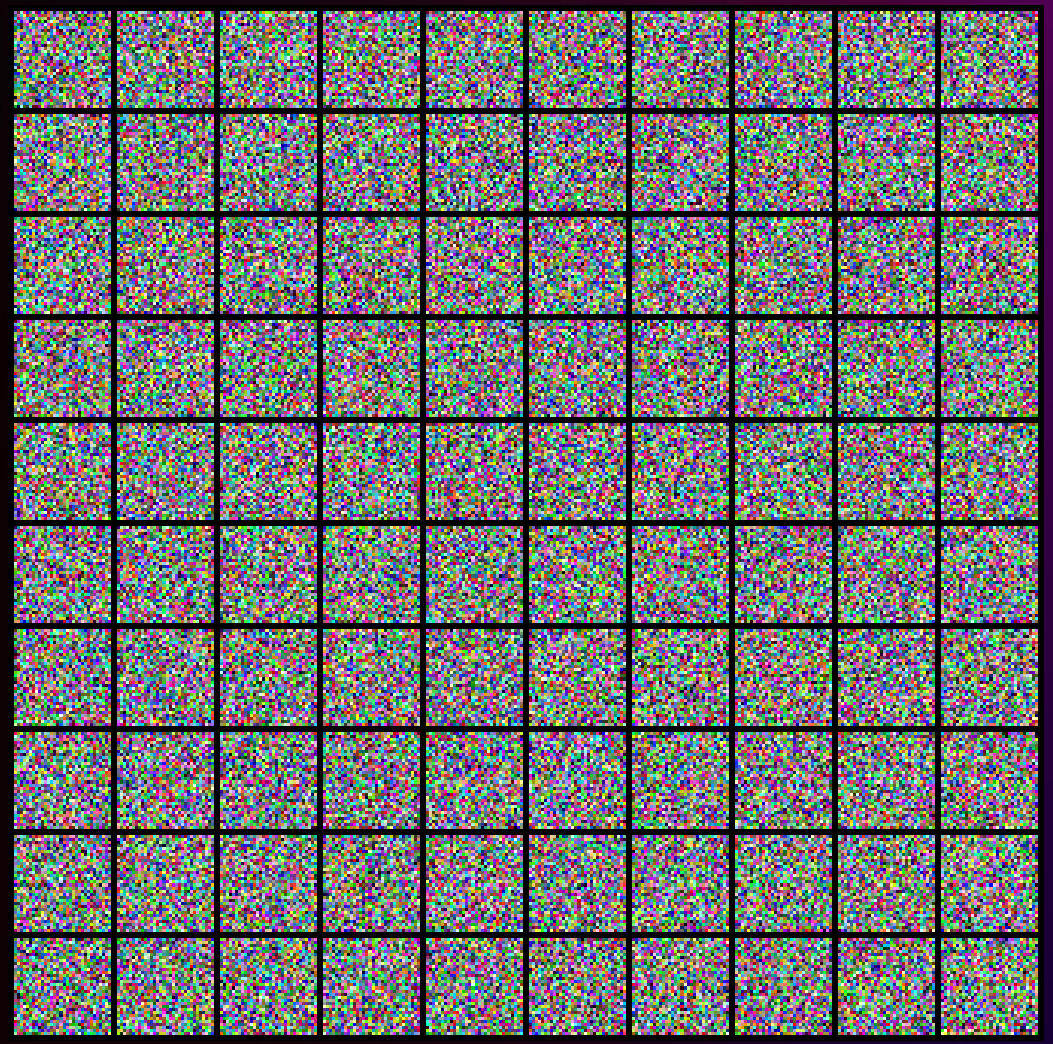
Y Song, S Ermon, NeurIPS 2019. D Prafulla, A Nichol, NeurIPS 2021.

Sampling from the prior: Annealed Langevin Dynamics

Sample $x \sim p(x)$

Each image is one sample

(CNN architecture: NCSNv2)



Y Song, S Ermon, *NeurIPS 2019*.

https://yang-song.net/blog/2021/score

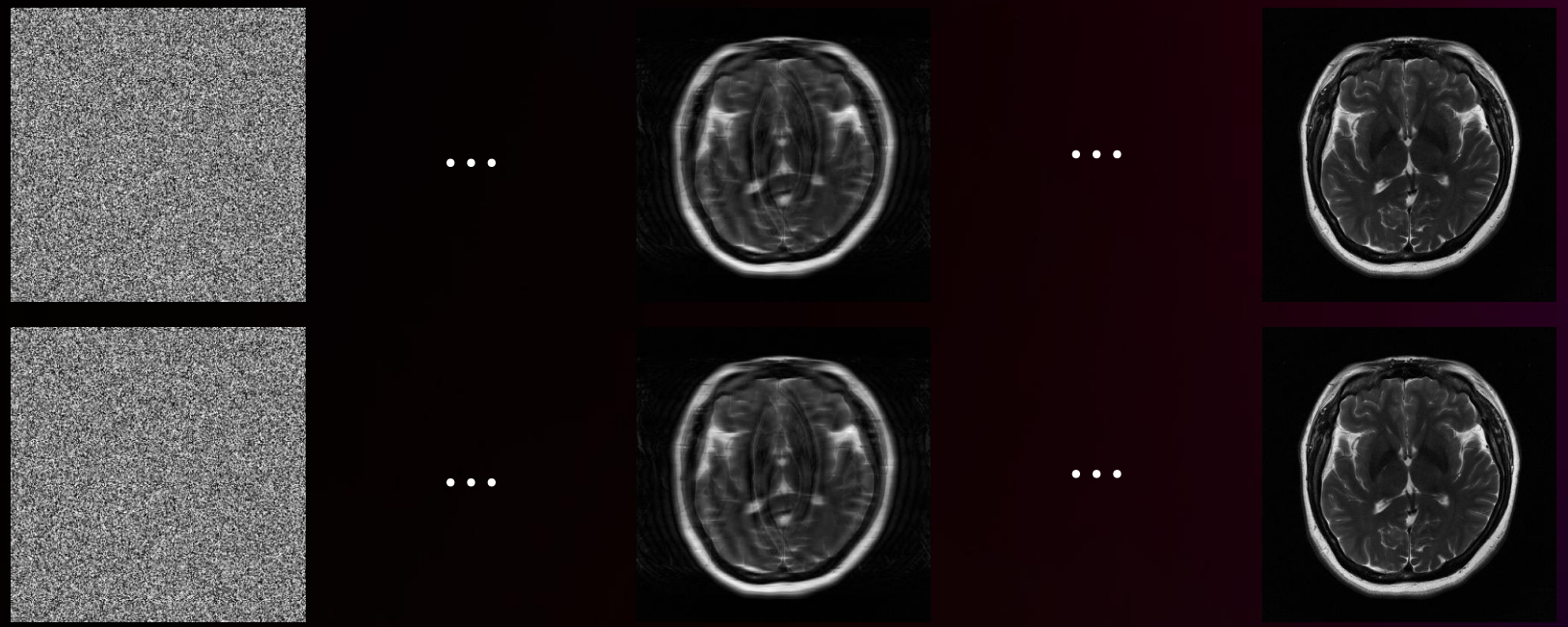
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Our approach: posterior sampling

Run Annealed Langevin Dynamics to sample from the posterior

$$\mathbf{x} \sim p(\mathbf{x}|\mathbf{y})$$



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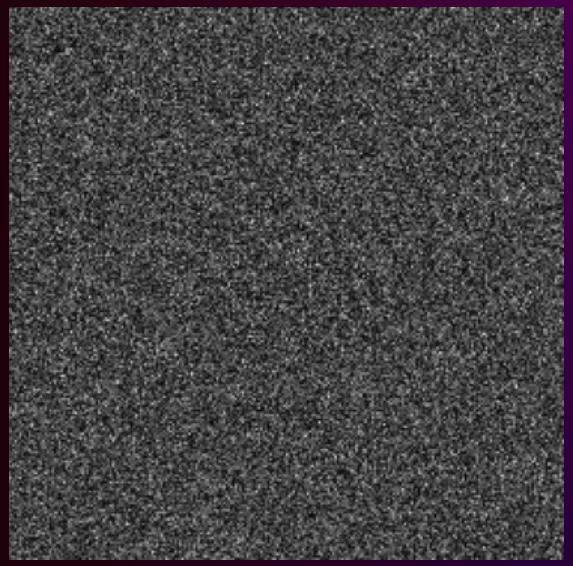
A Jalal et al., PMLR 2021. A Jalal, M Arvinte. et al., NeurIPS 2021

Our approach: posterior sampling

Pseudocode

```
score_net = MyCNN(...)
data_grad = DataConsistencyGrad(...)
...
x_hat = randn(...) # initialize x
for iter in range(max_iter):
  noise = anneal[iter] * randn(...)
  score = score_net(x_hat)
  grad = data_grad(x_hat, y, A)
  x_hat = x_hat + lr * (score + grad) + noise
```

Reconstruction



A Jalal, M Arvinte. et al., NeurIPS 2021

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Experimental results

We train NCSNv2 [Song ’20] on a subset of T2 brain scans from the publicly available fastMRI [Zbontar ’18] dataset.

Supervised baselines: MoDL [Aggarwal ‘18], E2E-VarNet [Sriram ‘20].

Test on several data shifts:

- Sampling pattern (acceleration, sampling direction)
- Anatomy (fastMRI knee, mridata.org abdominal)
- No method or hyperparameters are fine-tuned on ANY out-of-distribution sample

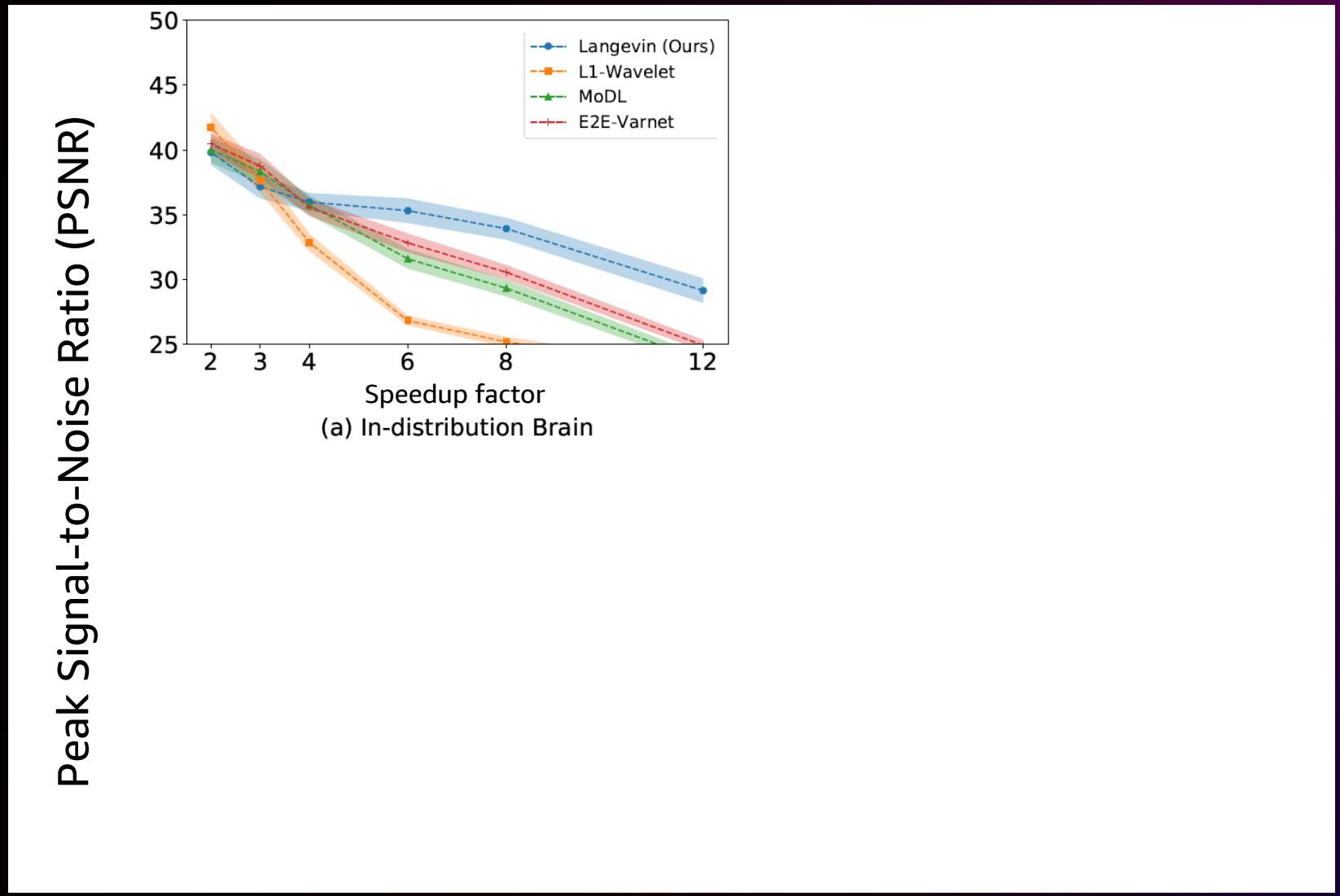
Code: https://github.com/utcsilab/csgm-mri-langevin

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Experimental results

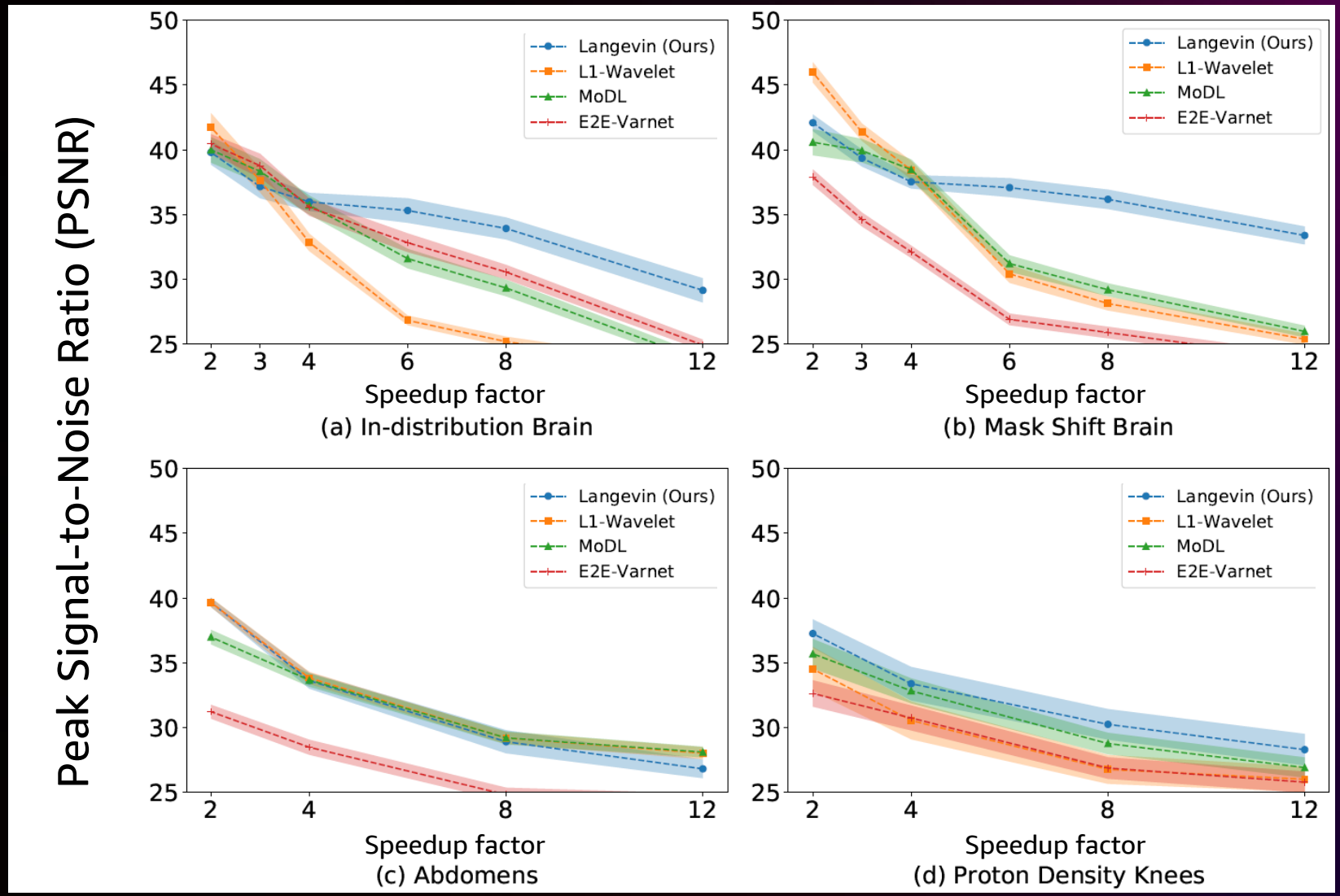
(higher is better)



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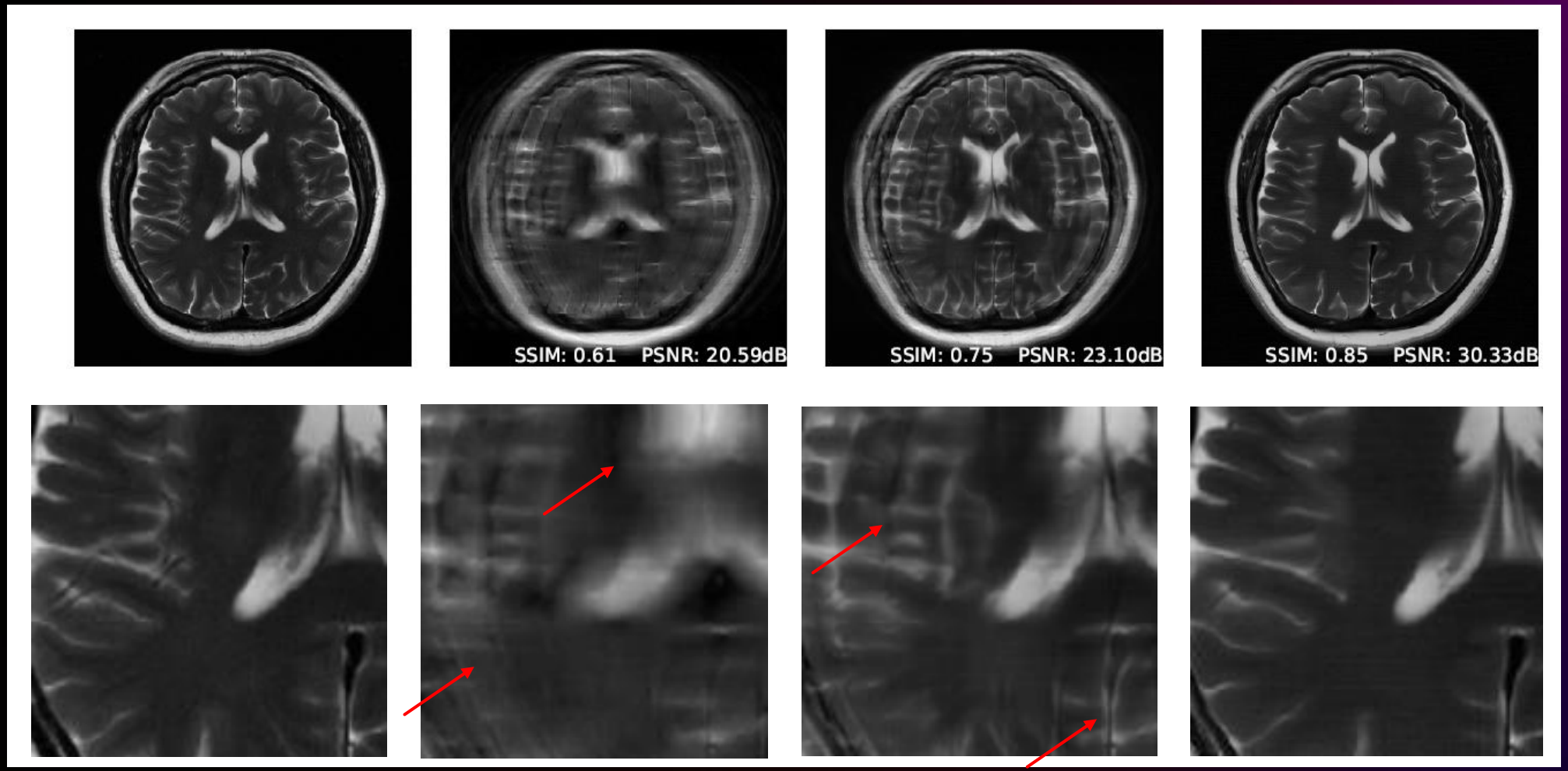
Experimental results

(higher is better)



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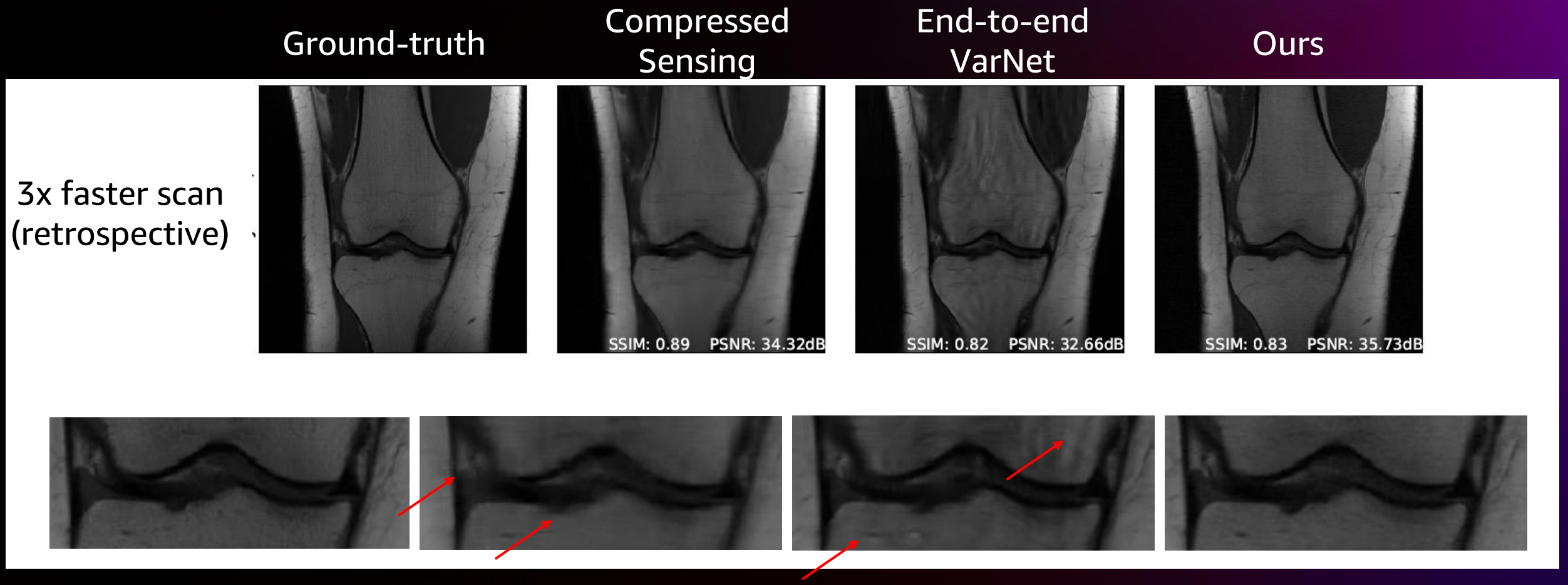
Experimental results – 10x faster scanning



Model was trained and tuned for brain MRI at 4x acceleration

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Experimental results – domain adaptation

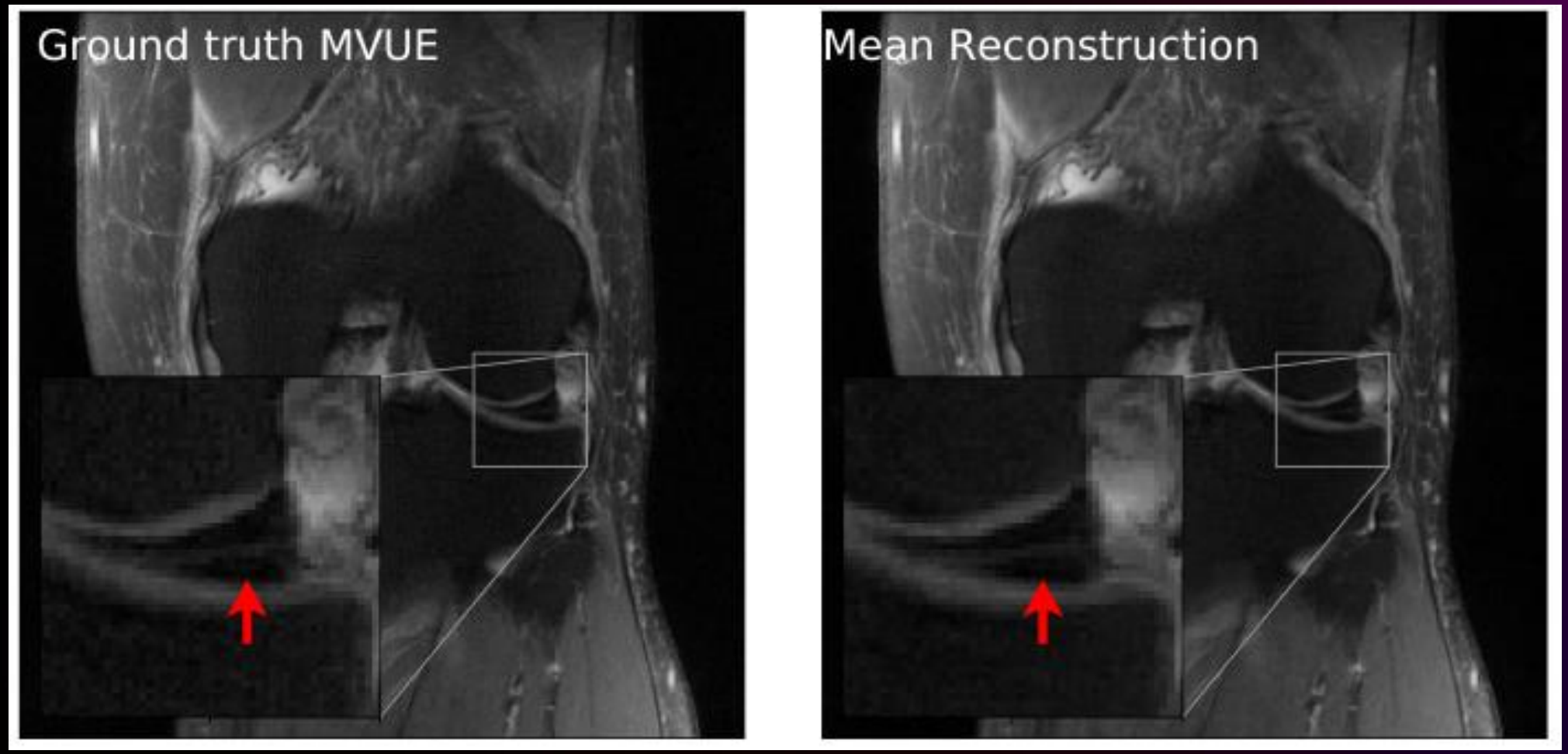


Model was trained and tuned for brain MRI at 4x acceleration

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Uncertainty estimation

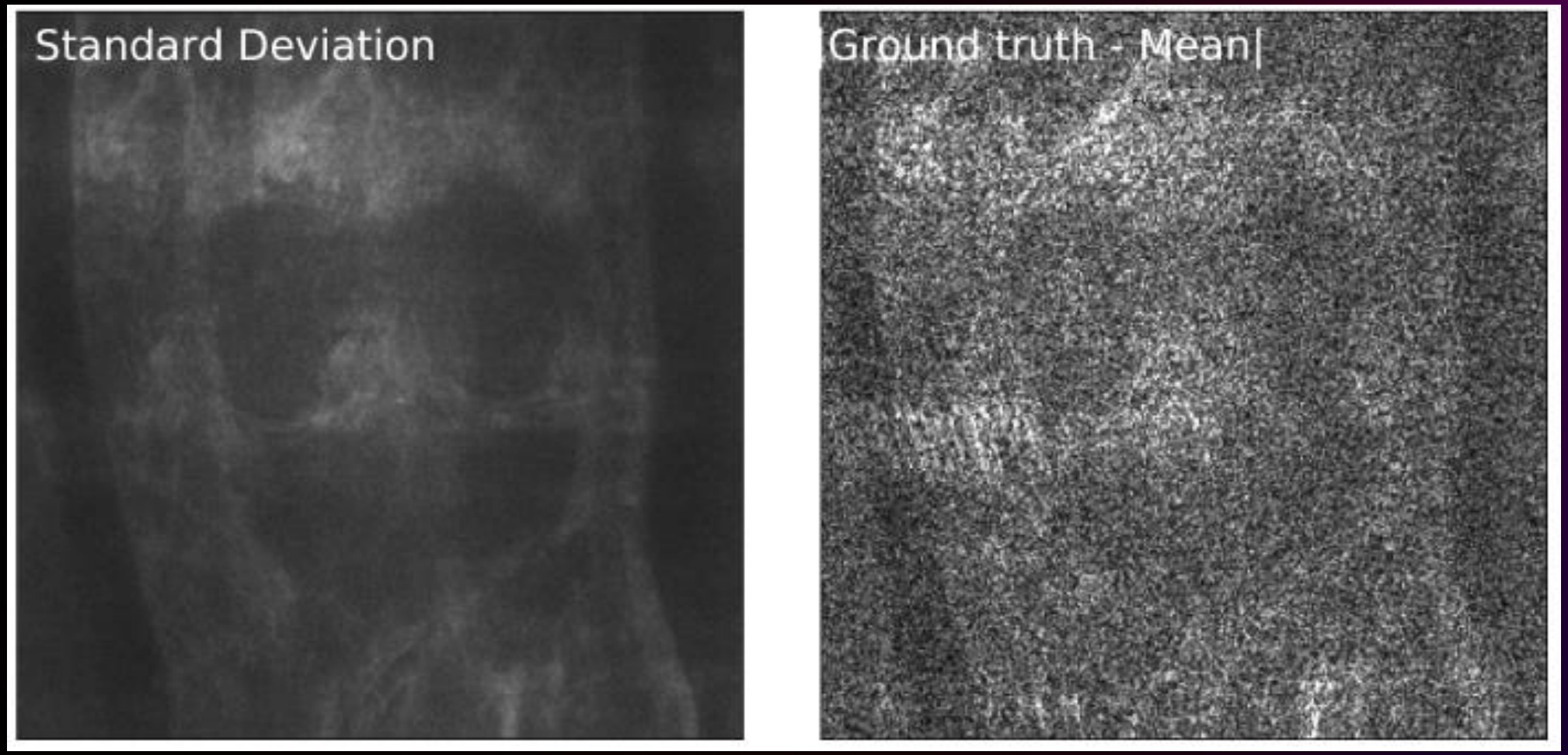
Multiple independent samples of the posterior, $\mathbb{E}[x|y]$



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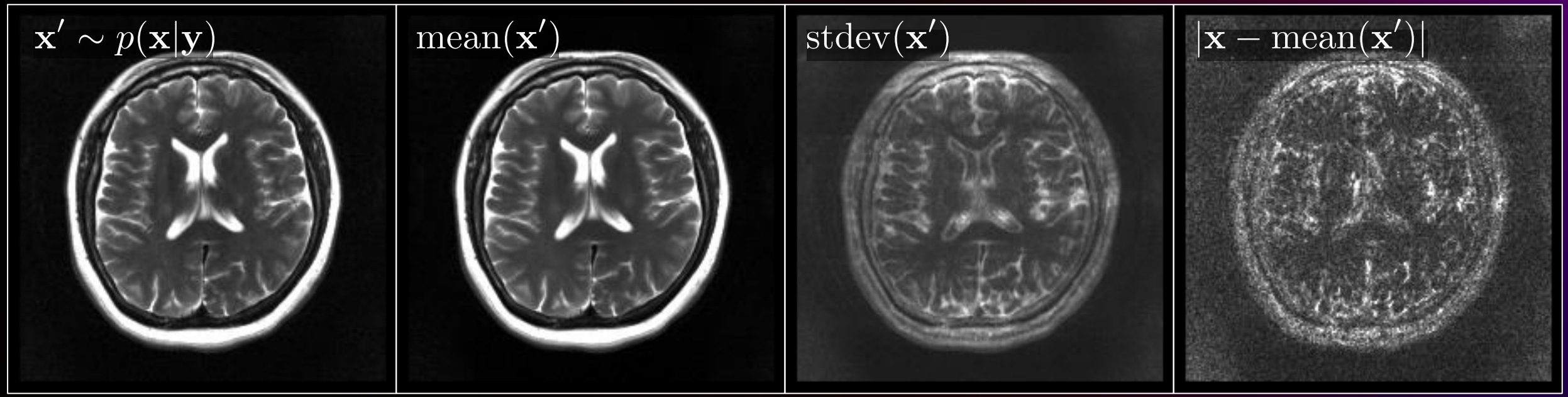
Uncertainty estimation

Multiple independent samples of the posterior, $\mathbb{E}[x|y]$



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Summary: MRI recon with score-based models

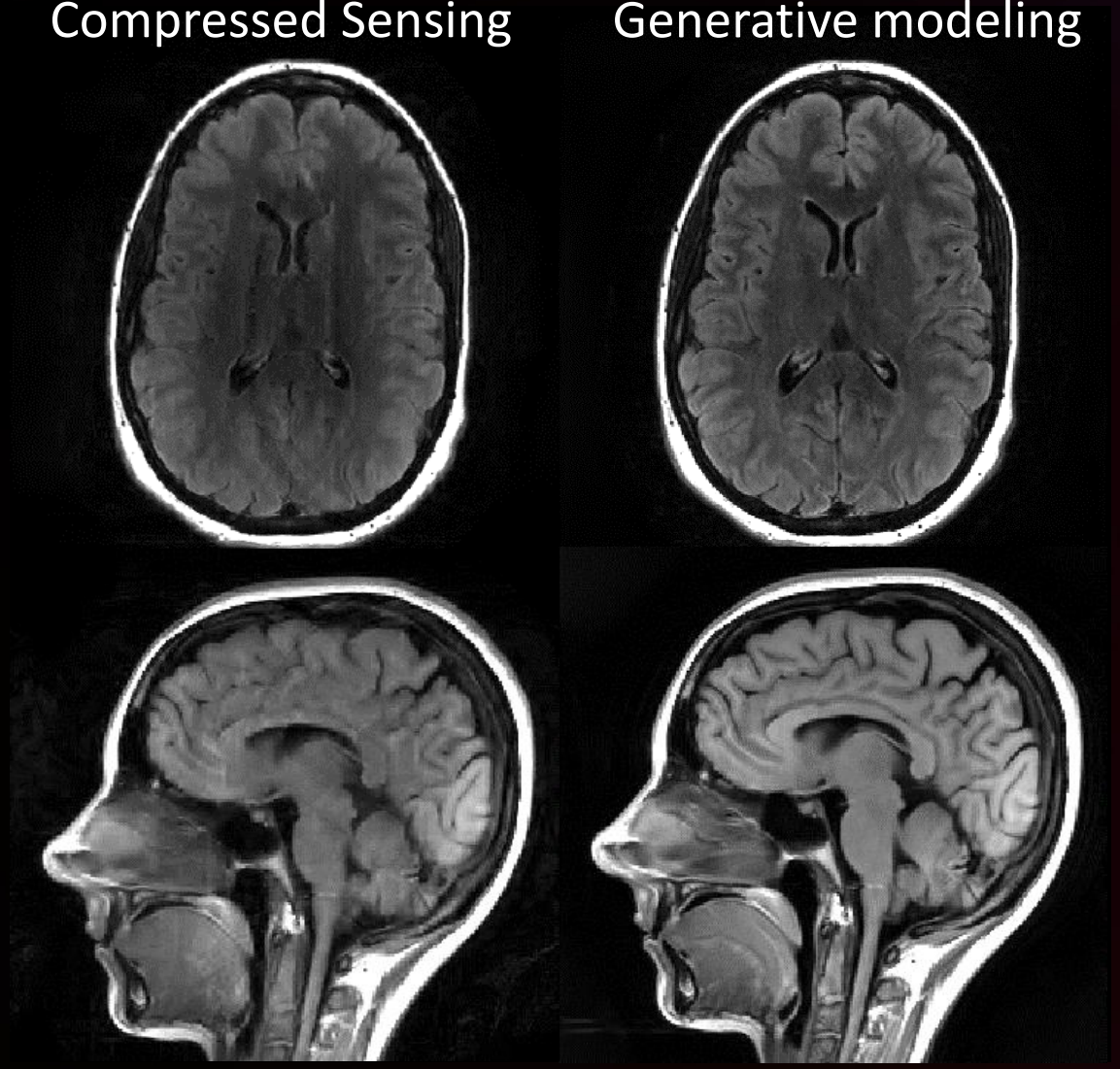


Reconstruction

Uncertainty estimation

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Prospective scanning at Dell Medical School



Multiple sclerosis protocol

3 Tesla wide bore scanner

Two healthy volunteers

4x faster scan

M Arvinte, et al, ISMRM 2022

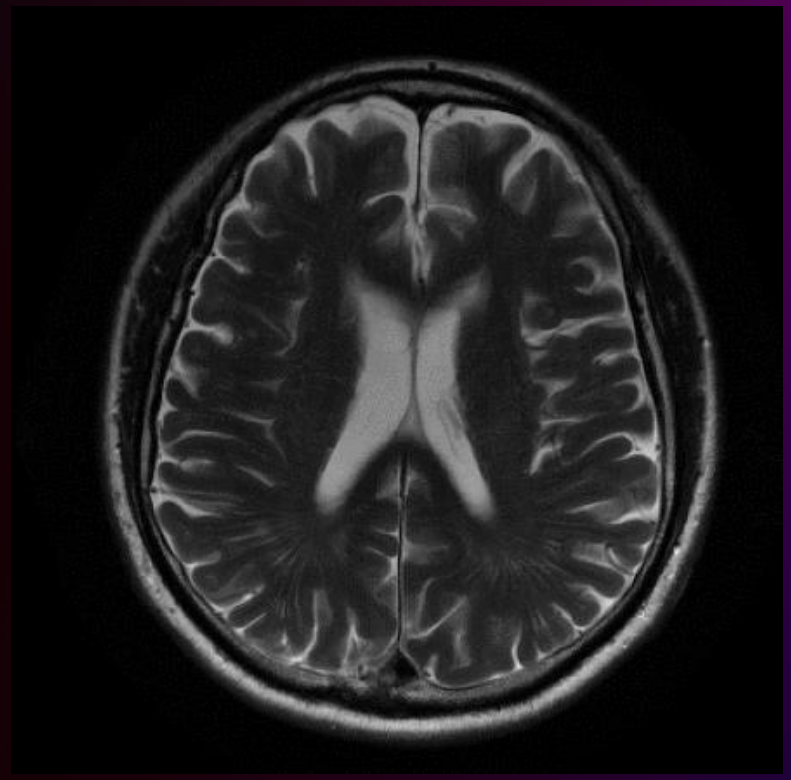
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Extending reconstruction to blind motion correction

Model rigid motion during the scan:

$$\mathbf{y} = \mathbf{A}_\theta \mathbf{x} + \text{noise}$$

Rotation and translation



The image prior is decoupled from the measurement model

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B Levac, A Jalal, JI Tamir, arXiv:2211.00199

Extending reconstruction to blind motion correction

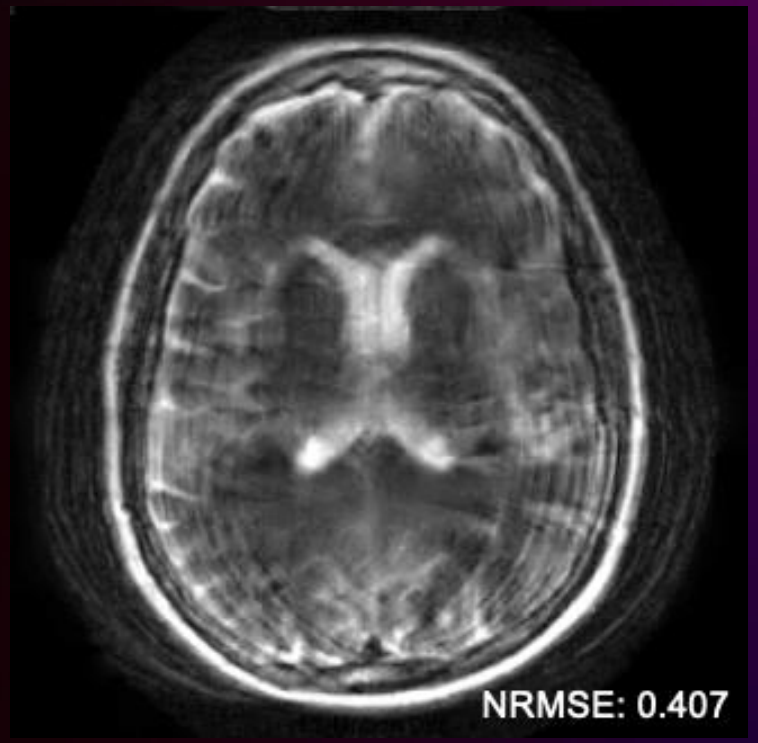
Model rigid motion during the scan:

$$\mathbf{y} = \mathbf{A}_\theta \mathbf{x} + \text{noise}$$

Rotation and translation

The image prior is decoupled from the measurement model

Reconstruction (blind to motion)



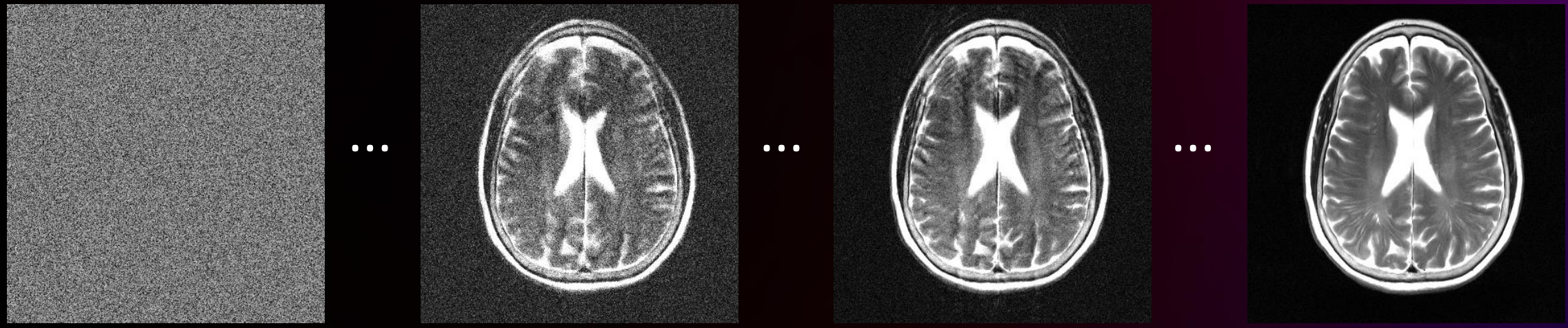
B Levac, A Jalal, JI Tamir, arXiv:2211.00199

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Joint posterior sampling over image and motion

Jointly solve for image and unknown motion

Use pre-trained deep score model for reconstruction



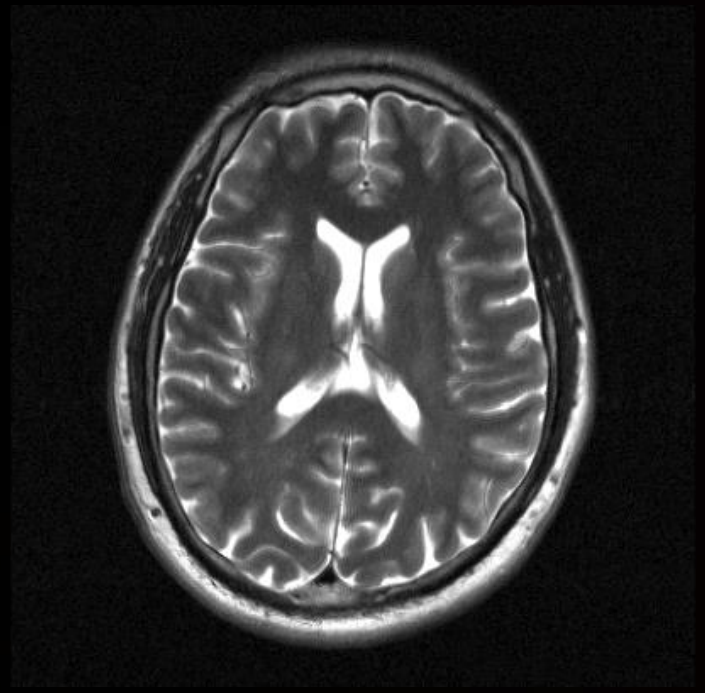
B Levac, A Jalal, JI Tamir, arXiv:2211.00199

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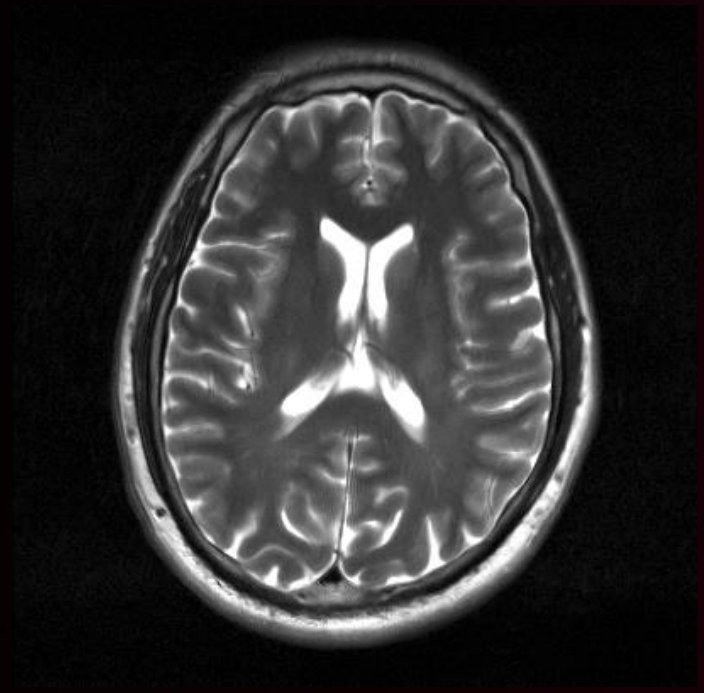
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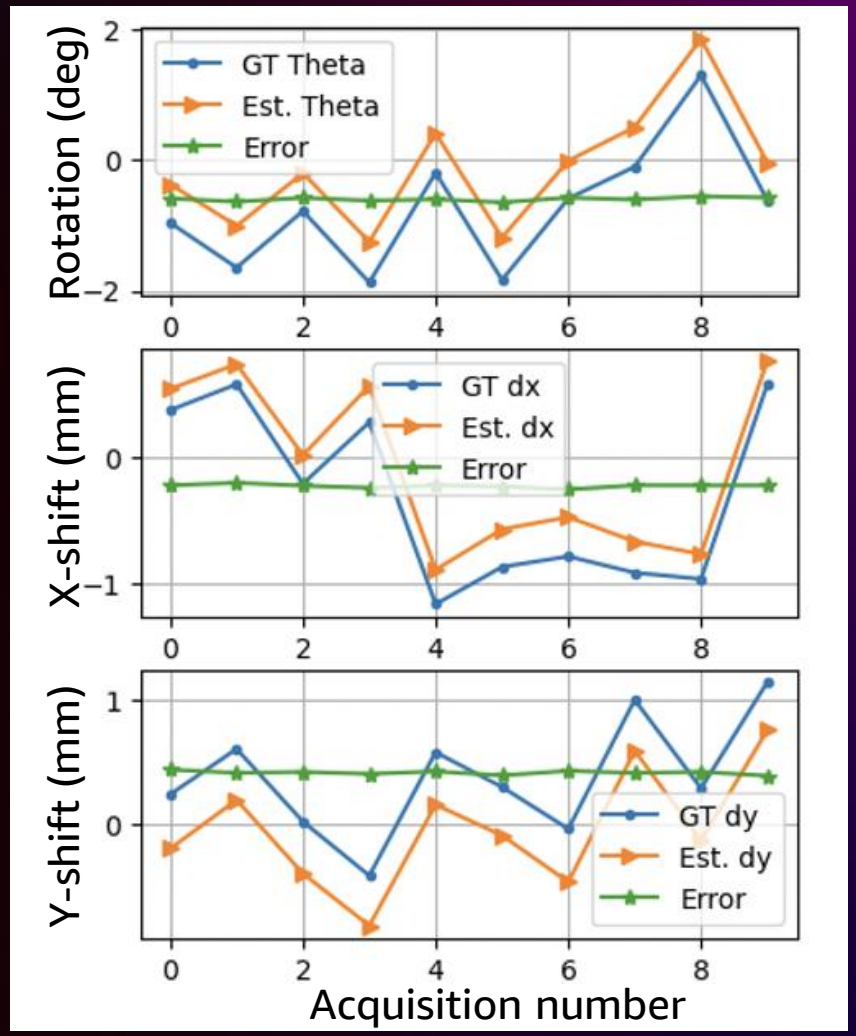
Experimental result: image recon + motion estimation

Ground-truth



Reconstruction





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B Levac, A Jalal, JI Tamir, arXiv:2211.00199

Conclusions

Robustness to test-time distribution is next major hurdle to deploying deep learning-based MRI reconstruction

1. Decoupling the image prior and measurement model can help
2. Posterior sampling comes with strong robustness guarantees
3. Accounting for the measurement process is critical

Clinical validation still needed

Code: https://github.com/utcsilab

Code



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