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Future of AI – Spotlight on Domain Knowledge

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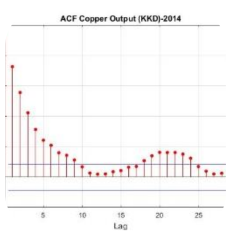
About ai.sys

Industrial Scale AI & Sys Engg



Geology to Mine to Mill

Generative AI (text analysis)

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About ai.sys

Algorithm Development

Machine Learning

Summarization

https://mining.utah.edu/ai.sys/

Evolution in Expectations in 20 years

- ✓ Magical set of tools that provide DEEP insight

http://www.suburbansoliloquy.com/2011/02/

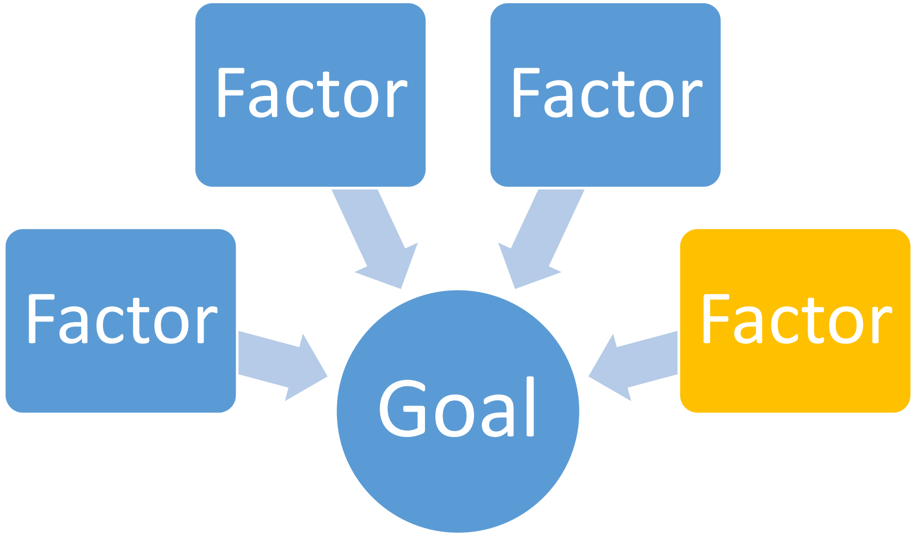
Clarifications on AI

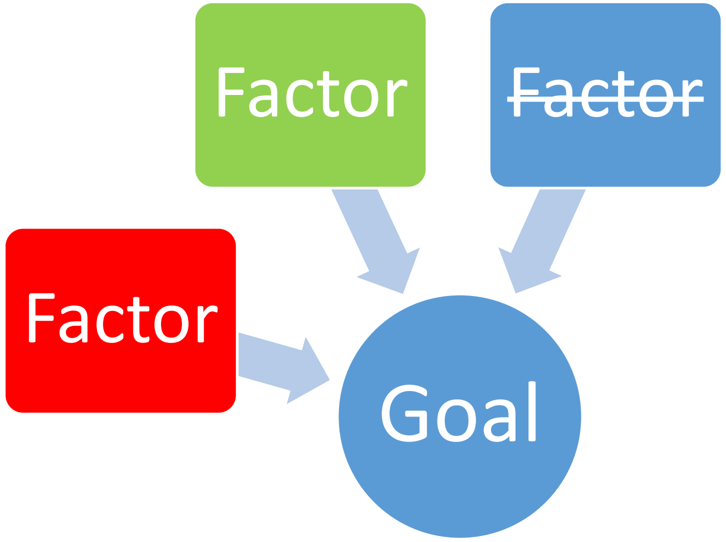
~~INTELLIGENCE~~

Currently,

AI can ONLY solve problems that humans can solve

~~Intelligence~~




Factor
~~Factor~~
Factor
Goal

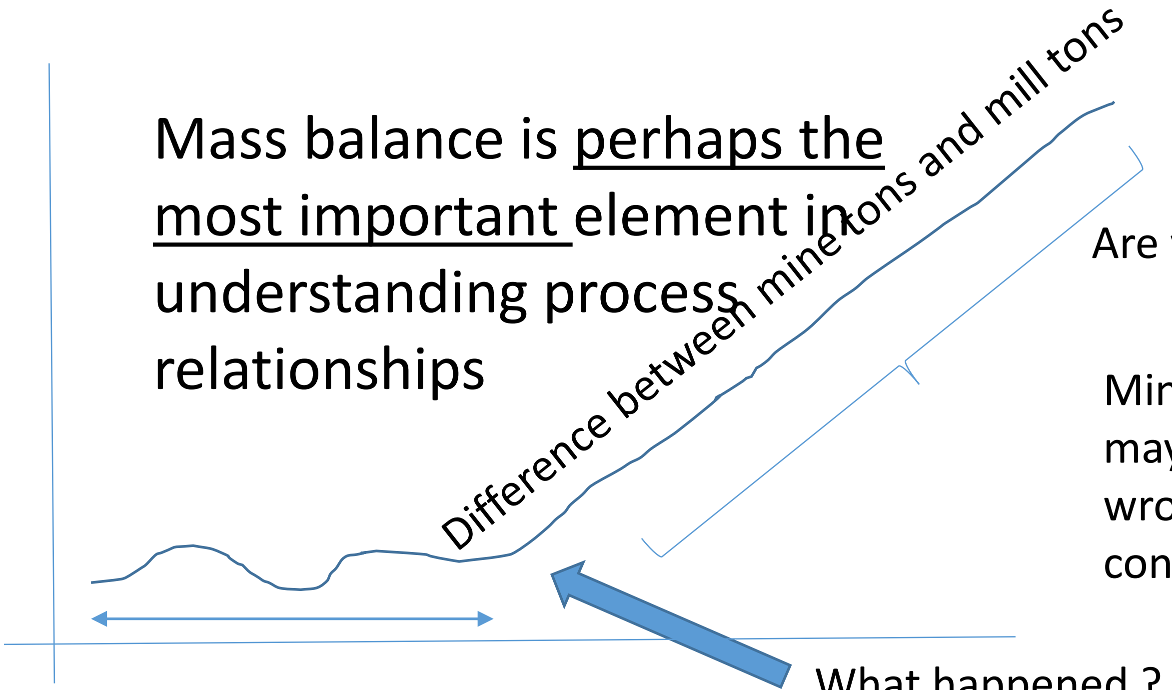
Challenges

More Data $\neq$ Good AI/ML

Industry focus is on quantity of data

Challenges: Data Quality

Mass balance is perhaps the most important element in understanding process relationships



Mine-Mill ML may produce wrong conclusions

At most mines, there is constant adjustment between mine and mill tonnages (to take into account moisture etc)

Challenges: Data Quality

- Problem areas with sensor data:
  - Dynamic weight measurement: Trucks, belt scale
  - Chemical: pH etc
  - Imaging/other: particle size

- Scope of Problems
  - $20 billion loss annual in US oil industry caused by sensor errors

Challenges: Data is not same as information

Data

Belt camera data says crushed rock particle size is high this morning

≠

Information

Rock is harder to grind this morning

Example:

More material from conveyor #4 → Difficult rock

But actual behavior of mill may be opposite some times

Bounded Problems

- Key factors/physics are known
- Lots of relevant data
- Data quality ok

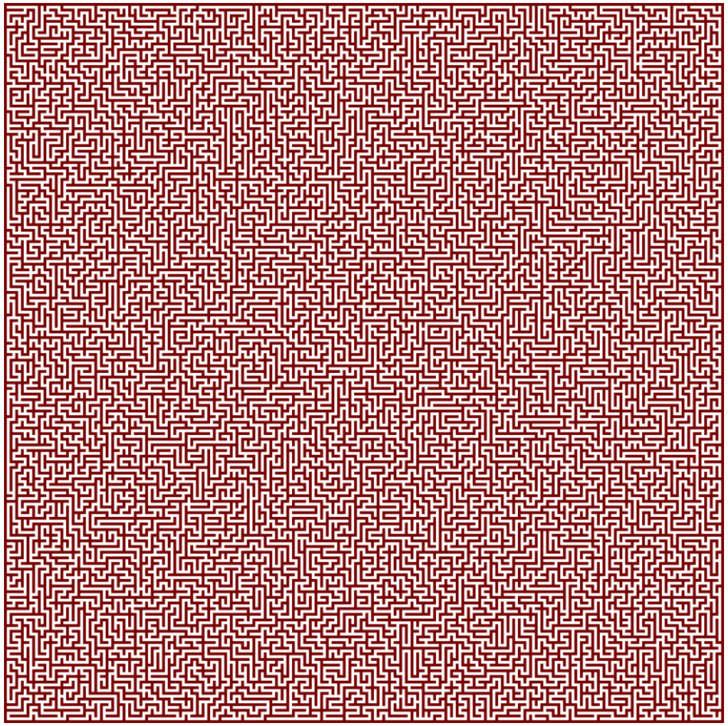
https://pixnio.com/furniture/chair-furniture-silhouette-darkness-window-chair-room

Examples:
- Face recognition
- Mill/processing plants

Bounded Problem Solutions

Turn on the light!
- Classic machine learning approaches
- Deep learning, random forests etc

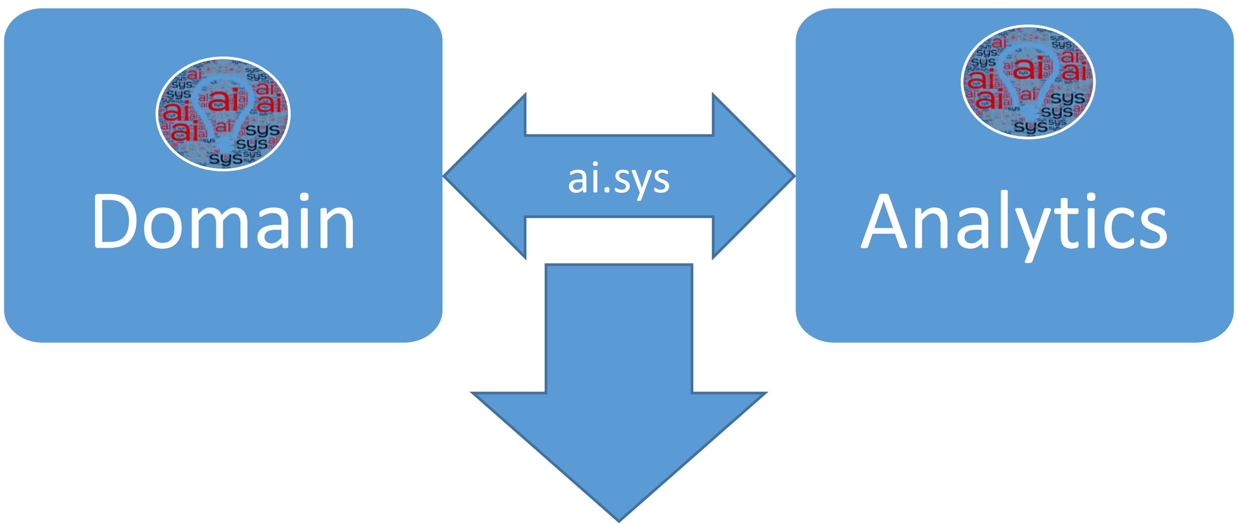
Unbounded Problems



- Often undefined or not defined well
- Physics may be known/expected, but difficult to quantify
- Not sure if data is adequate
- Beset with data quality issue

Good Example:
Mined material to mill throughput relationship

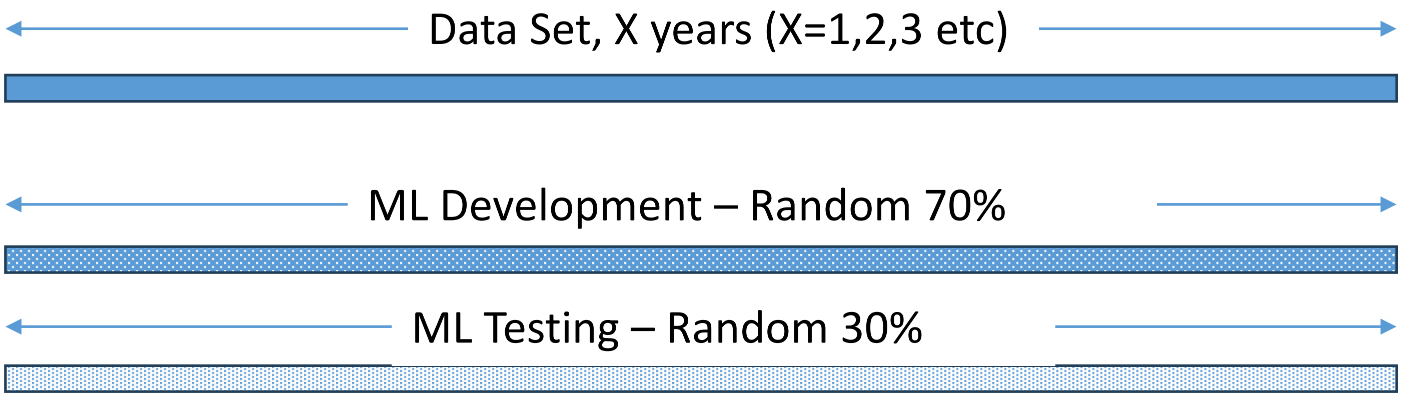
Skills Gaps:
Challenges



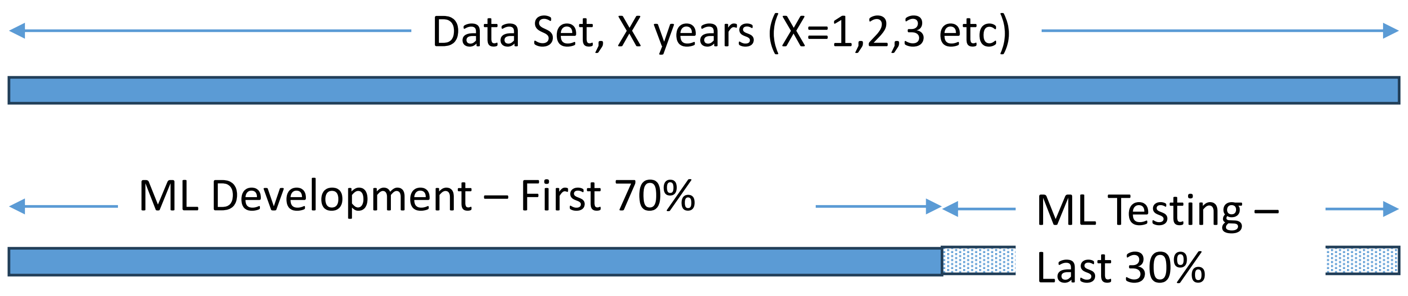
Wrong conclusions

When Domain expertise drives AI

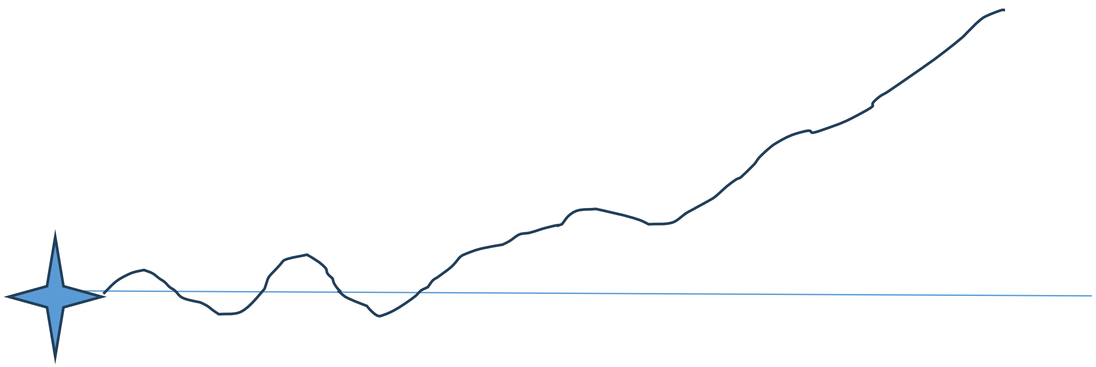
Traditional Approach



Traditional Approach Adaptive / Time Series



Typical Result
Difference between Model & Actual



Model Deployment

Ganguli Process

Data Set, X years (X=1,2,3 etc)

ML Testing – Last 96%

ML Development – First 4%

Prediction (r): 0.93

Opportunities
Modify Algorithm

Random Forest Modified

Mine	Data Set	Ganguli (R)	scikit (R)
Erdenet, Mongolia	Drillhole	0.83	0.78
Fort Knox, USA	SAG	0.96	0.96
Polymetal, Mexico	SAG*	0.89	0.86
Polymetal, Mexico	SAG	0.72	0.62

*Provided time series relationship

ChatGPT enhanced with domain expertise

Summarizing Accident Characteristics: *The nature of accidents could not be determined in most cases. However, they involve overexertion and accidents without injuries. Causes of accidents include falling materials (two counts), slip or fall of person (one count), and machinery (one count).*

Summarizing Accident Location: *Five accidents occurred in surface locations, while another five occurred in underground locations. Accidents occurred in six coal mines and four metal mines.*

Summarizing Injuries: *The nature of injuries detected in accidents includes nine instances of physical injuries primarily. A majority of cases involved one injury. The body parts identified as injured include the torso (four counts), hand (three counts), and shoulders (one count). The sources of injury consist of four instances of rock, coal, ore, waste, and three instances of hand tools. The impact on the ability to work includes days away from work (six counts), no days away from work (three counts), and minor incidents (one count).*

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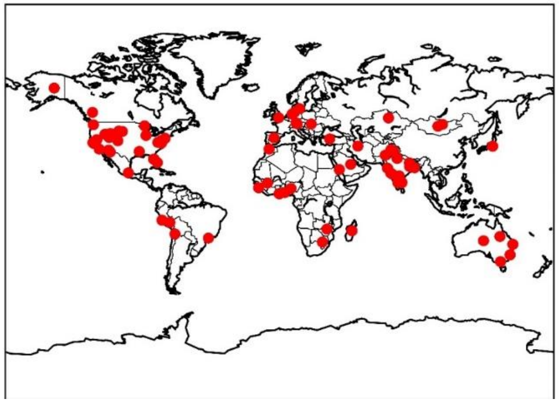
Domain Expertise & Gen AI

Model	Accuracy% (Standard Evaluation Metrics) ChatGPT	Accuracy % (Standard Evaluation Metrics) PSM
Accident Type	[illegible]	[illegible]
Classification	29	90
Location	[illegible]	[illegible]
Mining Equipment	34	78
Number of Injuries	86	100
Injury Source	23	76
Injury Nature	[illegible]	[illegible]
Injury Body Part	[illegible]	[illegible]
Degree of Injury	26	80
Activity	51	76
Mine Type	23	90
Average Values	49	87

FREE



UteAnalytics

http://mining.utah.edu/ai.sys

Recommendations

- Chase bounded problems
  - "Micro-AI"
- Do not start a large AI initiative:
  - Without well defined goals
  - Without confidence about the data
- Start small, and let it grow organically
- Don't forget systems engineering
  - You are more likely to save $$ through that immediately

As the romance matures …

- Companies will evaluate AI, and not just be "impressed" by whizbang claims
- Time for domain experts to speak up
  - The only natural intelligence ➔ YOU!

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Questions?

- Biography
- Dr. Rajive Ganguli is the Malcolm McKinnon Professor of mining engineering at the University of Utah. He has both academic and industry experience, having also worked at the University of Alaska Fairbanks (as professor), Jim Walter Resources (as mine foreman) and Hindustan Copper Limited (as mine engineer). He has been applying AI since the 1990s, long before it was cool to do so in mining. He has applied AI on numerous projects around the world, on topics ranging from birds to mining. His chapter on the use of natural language processing for analyzing safety narratives was published in 2024 in the SME Mine Safety Handbook. He was inducted into the Alaska Innovators Hall of Fame in 2017 for the development of a mill simulator. His software, UteAnalytics, has been downloaded from 28 countries
- rajive.ganguli@utah.edu

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