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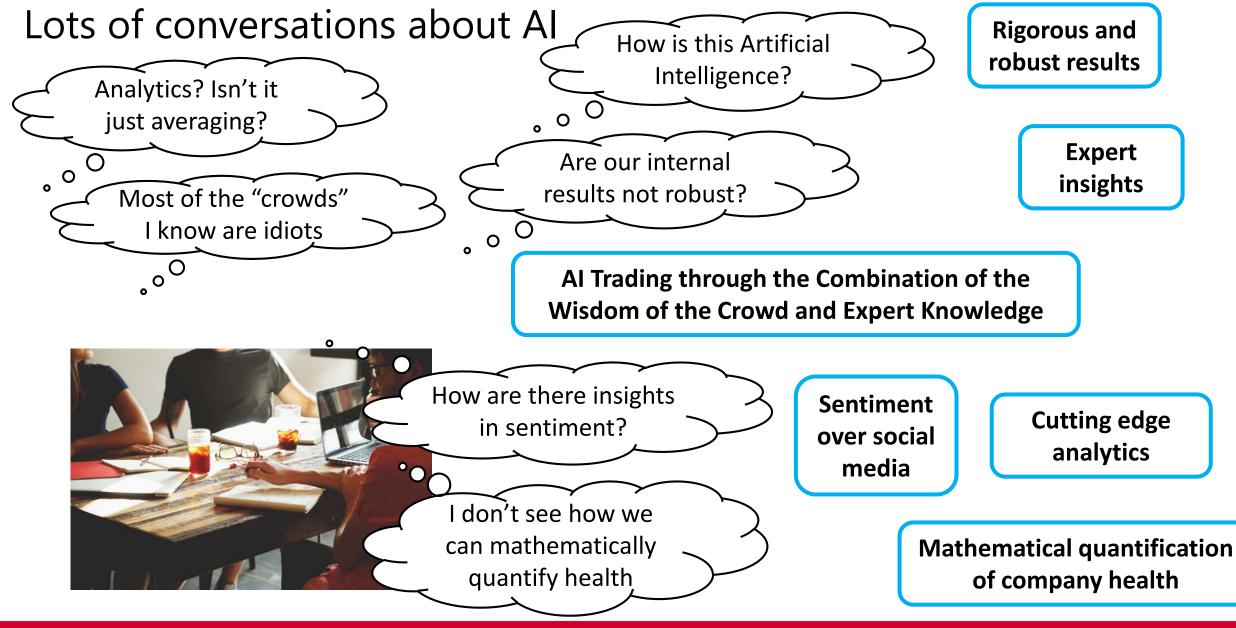
# Artificial Intelligence

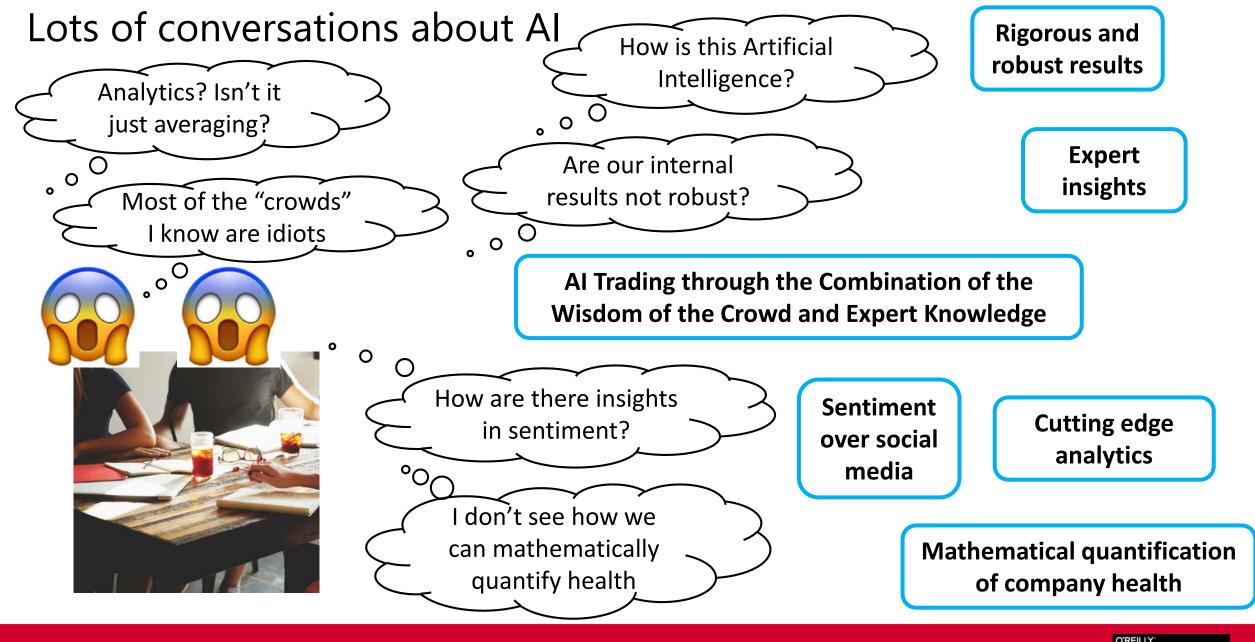
# A Practical Guide to Conducting an Al Snake Oil Sniff Test

Josh Joseph jj@alphafeatures.com

Chief Science Officer, Alpha Features

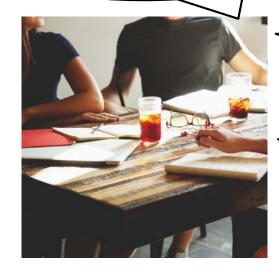
oreillyAlcon.com #OReillyAl





Awesome they have machine learning in the cloud!

Joe was just talking about how random forests are super cool



Smart team!

What a great school they are from!

Rigorous and robust results

**Expert** insights

Al Trading through the Combination of the Wisdom of the Crowd and Expert Knowledge

And they're doing that!
Of experts! In the cloud!

Sentiment over social media

Cutting edge analytics

<Insert super important
business decision being made>



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<Insert super important
business decision being made>

Rigorous and robust results

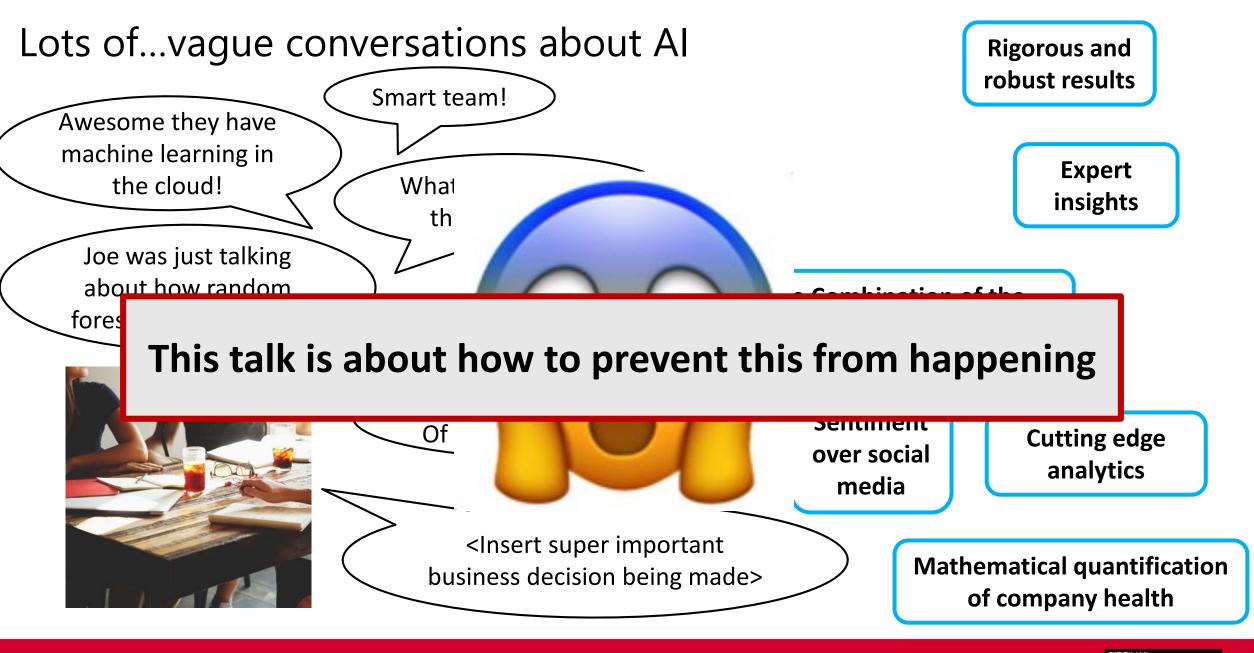
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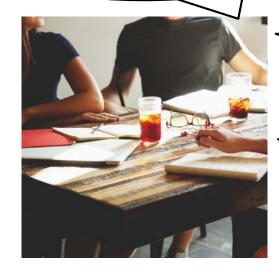






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# Maybe that's just the way it is? We know there's a lot of hype...



NEW YORKER

**CURRENCY** 

#### THE HYPE—AND HOPE—OF ARTIFICIAL INTELLIGENCE

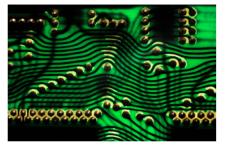
By Om Malik August 26, 2016





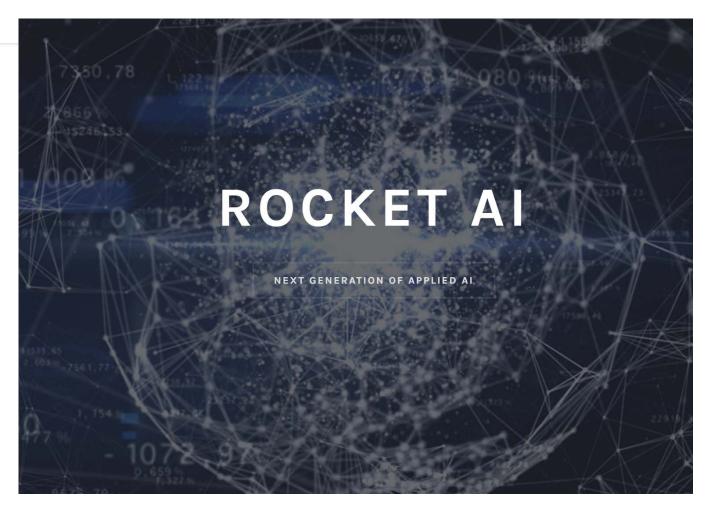


**F** arlier this month, on his HBO show "Last Week Tonight," John Oliver skewered media companies' desperate search for clicks. Like many of his bits, it became a viral phenomenon, clocking in at nearly six million views on YouTube. At around the ten-minute mark, Oliver took his verbal bat to the knees of Tronc, the new name for Tribune Publishing



Much like "the cloud," "big data," and "machine learning" before it, the term "artificial intelligence" has been hijacked by marketers and advertising copywriters.

Photograph by Erich Hartmann / Magnum





# Maybe that's just the way it is? We know there's a lot of hype...



#### What can Al do for your business?

1 message

Comcast Business <reply@notice.comcastbusiness.com>
Reply-To: Comcast Business <CB\_Replies@comcastbusiness.com>
To:

Wed, Aug 30, 2017 at 12:36 PM



COMCAST BAB BUILT FOR BUSINESS

# PRODUCTIVITY@WORK

**AUGUST 2017** 

**NAVIGATING THE SMB TECH REVOLUTION** 

Artificial intelligence (AI) has been the darling of science fiction writers for decades, but it's fiction no more—and is now becoming accessible to small and





# While it's easy to make fun of the hype...there are repercussions



July 12, 2017

# IBM (IBM)

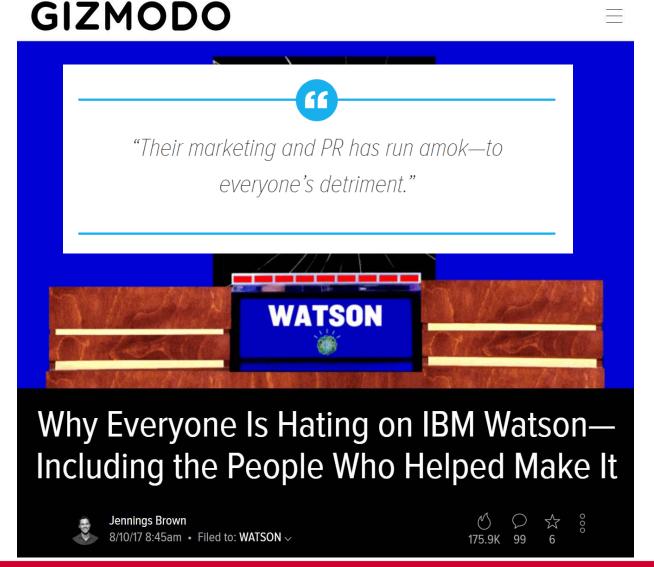
# Creating Shareholder Value with AI? Not so Elementary, My Dear Watson

#### **Key Takeaway**

Our checks suggest that while IBM offers one of the more mature cognitive computing platforms today, the hefty services component of many Al deployments will be a hindrance to adoption. We also believe IBM appears outgunned in the war for Al talent and will likely see increasing competition. Finally, our analysis suggests that the returns on IBM's investments aren't likely to be above the cost of capital. Reiterate Underperform.

**Al is the New Electricity....**Our checks confirm that a wide range of organizations are exploring incorporating Al in their business, mostly using Machine and Deep Learning for speech and image recognition applications.

...But Competitive Environment Doesn't Favor IBM. Our checks suggest that IBM's Watson platform remains one of the most complete cognitive platforms available in the marketplace today. However, many new engagements require significant consulting work to gather and curate data, making some organizations balk at engaging with IBM. As outlined





#### So what do we do?

 $\equiv$  FORTUNE

**SUBSCRIBE** 

ARTIFICIAL INTELLIGENCE

#### Beware the Hype of Artificial Intelligence

Jonathan Vanian Jun 23, 2017







Artificial intelligence has made great strides in the past few years, but it's also generated much hype over its current capabilities.

That's one takeaway from a Friday panel in San Francisco involving leading AI experts hosted by the Association for Computing Machinery for its 50th annual Turing Award for advancements in computer science.

Michael Jordan, a machine learning expert and computer science professor at University of California, Berkeley, said there is "way too much hype" regarding the capabilities of so-called chat bots. Many of these software



# Don't believe the hype when it comes to Al

Artificial intelligence may be subject to more hype than any other field. While this creates funding opportunities, it could also damage Al's long-term potential

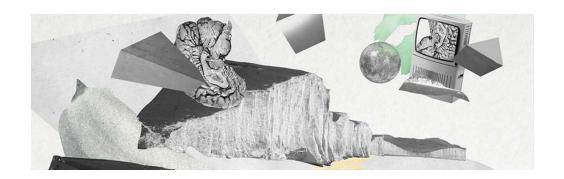
By LUKE DORMEHL

18 Feb 2017













Frank Chen Follow

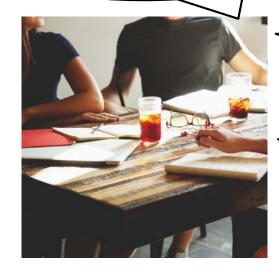
Partner at Andreessen Horowitz. Writes about tech, startups, venture investing, science, the future. Likes ex...
Jun 26 · 3 min read

# In a few years, no investors are going to be looking for AI startups

But the reason I believe that no investor will be funding startups calling themselves AI-powered startups (and no startup CEO will differentiate themselves as an AI-first company like Google) is because investors will assume the startup is using the best available AI techniques to solve the problem they are solving.

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# Many, many experiences working through this

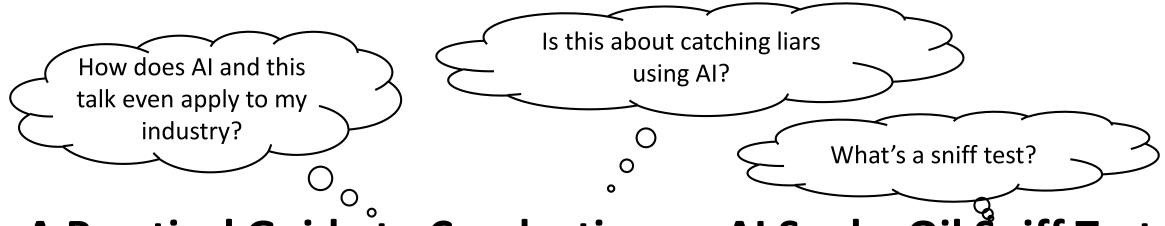
- Wide range of ML methods for my PhD at MIT
- Variety of AI/ML consulting work: biotech, co-working space pricing, robotics
- Alpha Features and previous propriety trading experience evaluating dozens "analytics/signals"
- Due diligence on over a hundred AI/ML hedge funds

...so you can imagine there's been a *lot* of



and I'd like to share our process for working through it



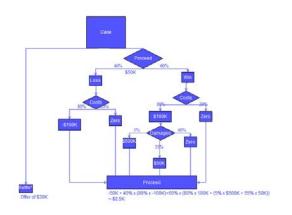




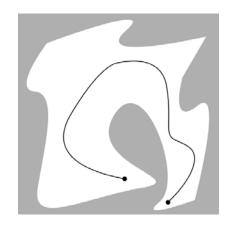


A hodgepodge of rules discovered somehow (that can be implemented in a computer)



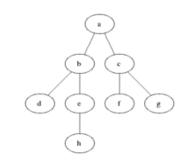


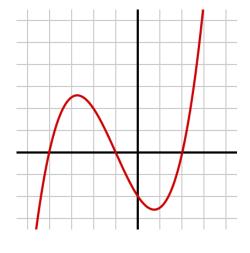
```
If (boolean condition) Then
     (consequent)
Else
     (alternative)
End If
```



An amalgamation of rules discovered somehow (that can be implemented in a computer)

$$orall x orall y(P(f(x)) 
ightarrow 
eg(P(x) 
ightarrow Q(f(y),x,z)))$$





\*pictures from wikipedia



An amalgamation of rules discovered somehow (that can be implemented in a computer)

I'm going to focus on machine learning for most of the talk

An amalgamation of rules discovered by **making assumptions and following principles** which allow us to believe something about the future performance (that can be implemented in a computer)



The **liar** cares about the truth and attempts to hide it; the **bullshitter** doesn't care if what they say is true or false, but rather only cares whether or not their listener is persuaded.

-Harry Frankfurt

# A Practical Guide to Conducting an Al Snake Oil Sniff Test

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# A Practical Guide to Conducting an Al Snake Oil Sniff Test

An amalgamation of rules discovered somehow (that can be implemented in a computer)

30 minute to 2 hour meeting

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An amalgamation of rules discovered by **making assumptions and following principles** which allow us to believe something about the future performance (that can be implemented in a computer)





concrete process, questions, tips

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30 minute to 2 hour meeting





# Components of a Productive ML Sniff Test

- Surface-level understanding of some core ML concepts
- Sniff test procedure
- General tips



# A Quick Brush of Core ML Concepts

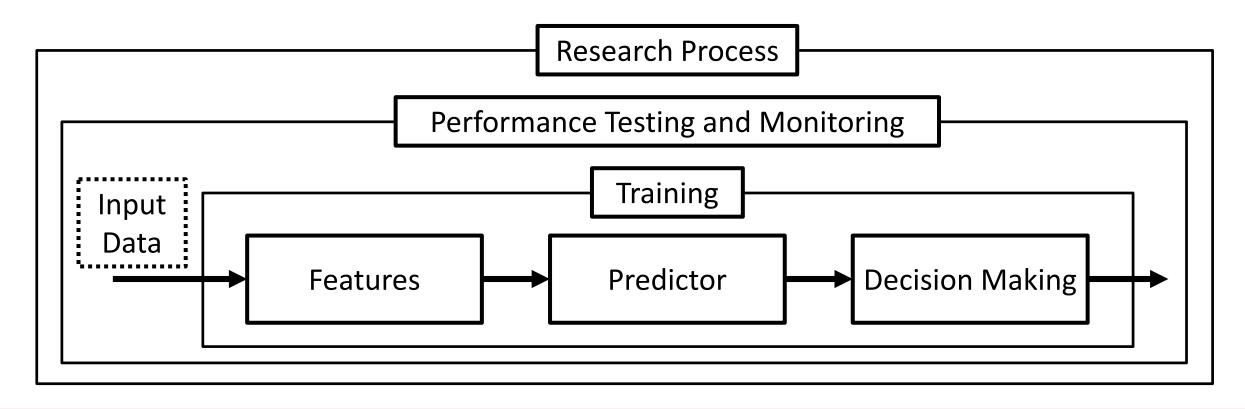
- Generalization
  - How will my system perform when I turn it on?
  - To the future, changing environment, new users, additional markets, different geographies, etc.
- The amalgamation of rules inside these systems make assumptions
  - Not knowing the assumptions you're making is gambling
- No such thing as zero human involvement



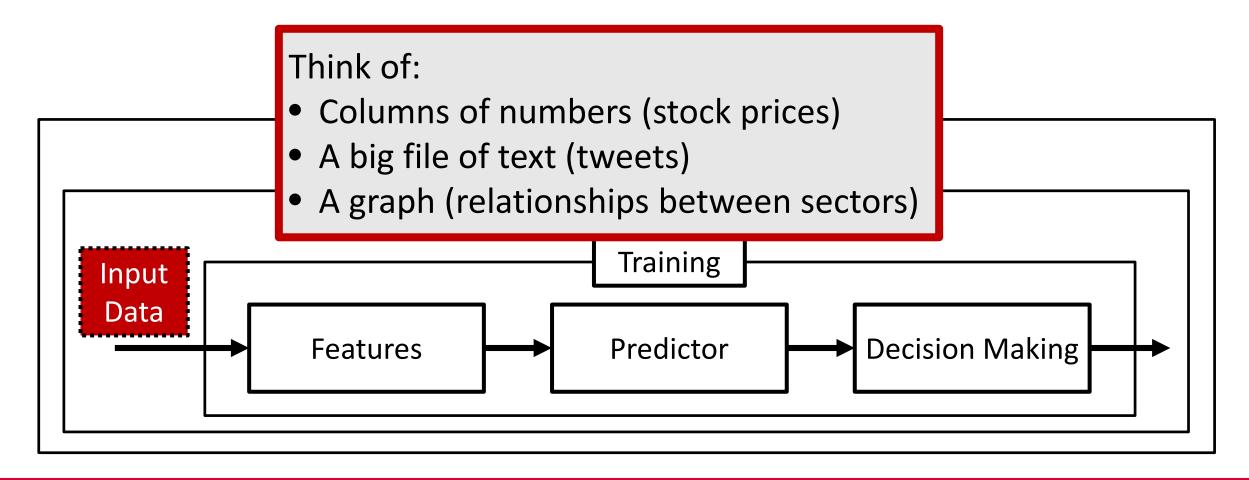
# Components of a Productive ML Sniff Test

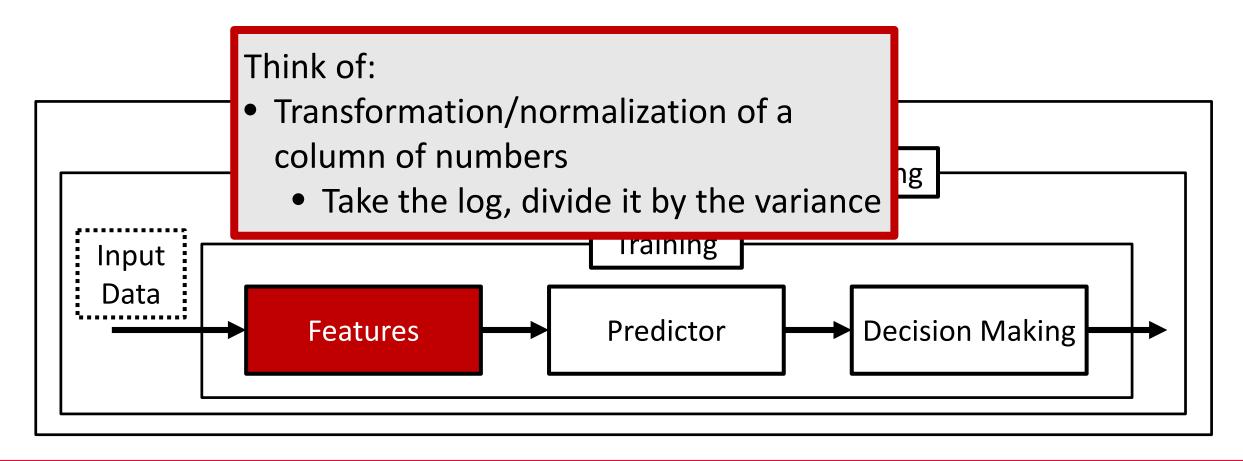
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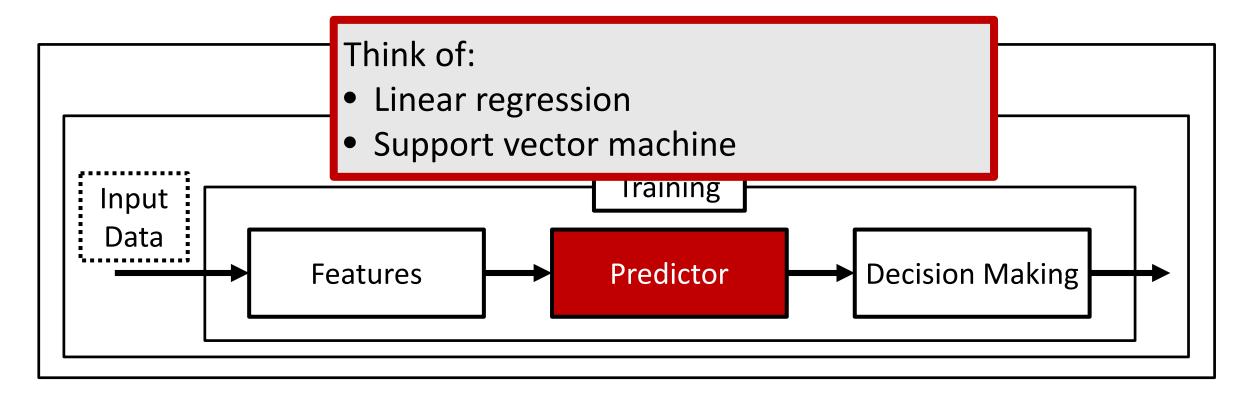




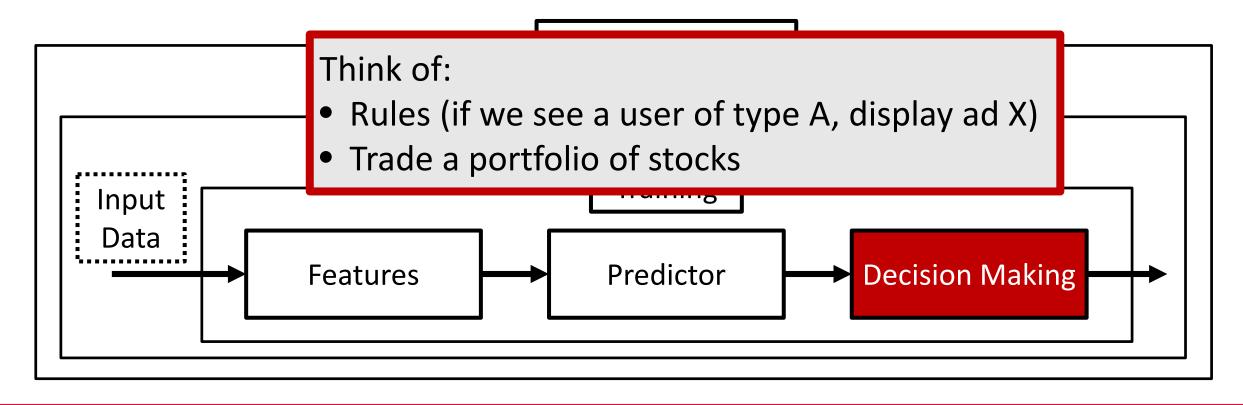




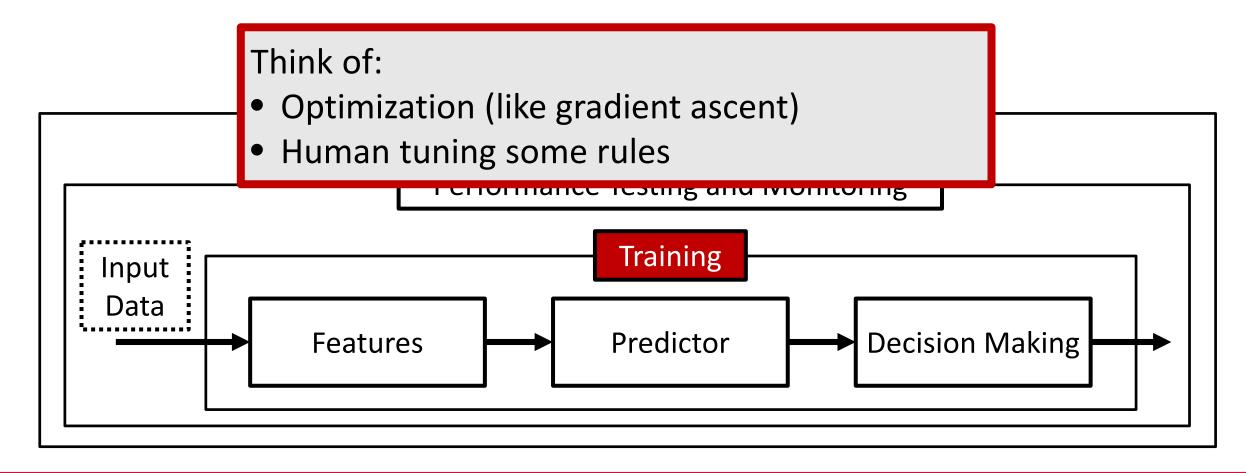








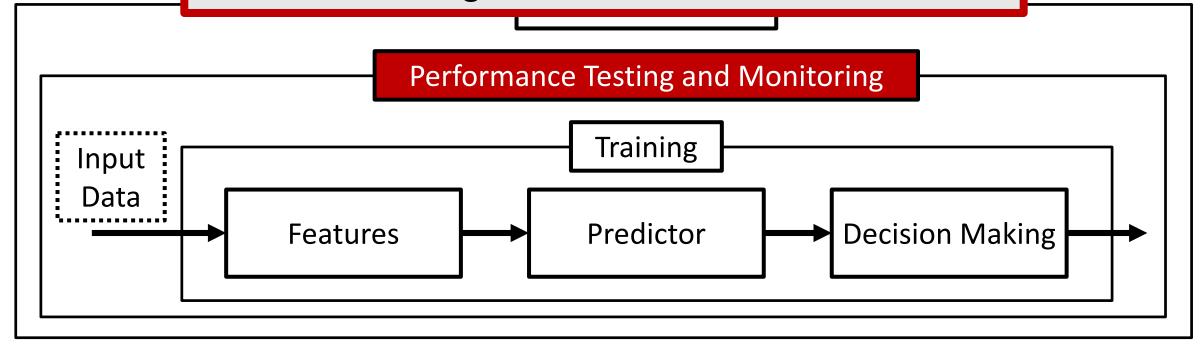






#### Think of:

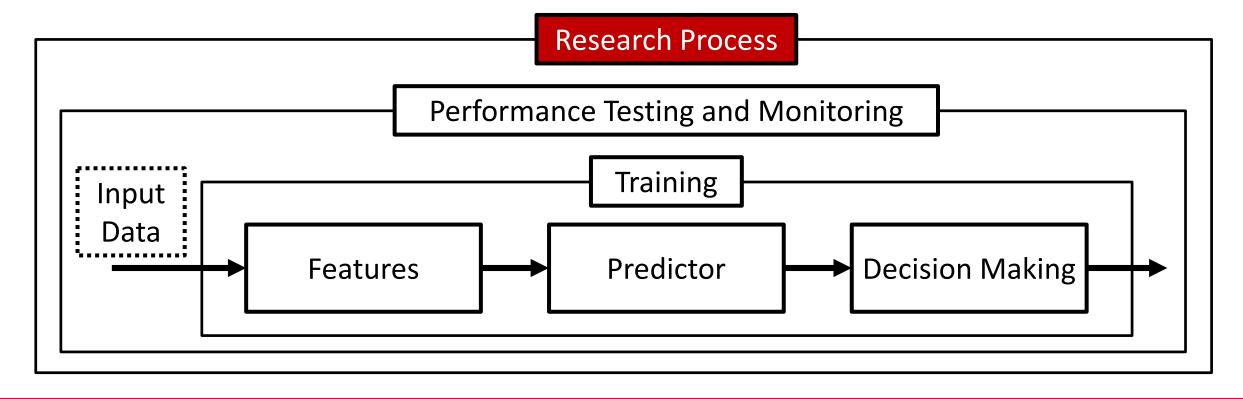
- Computing out-of-sample performance
- Comparing live performance to a historical estimate
- Statistical testing



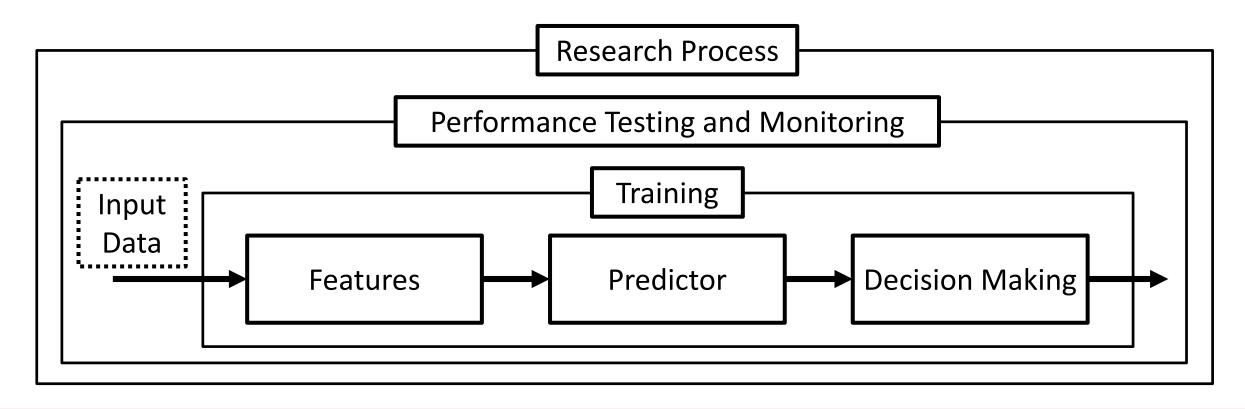


#### Think of:

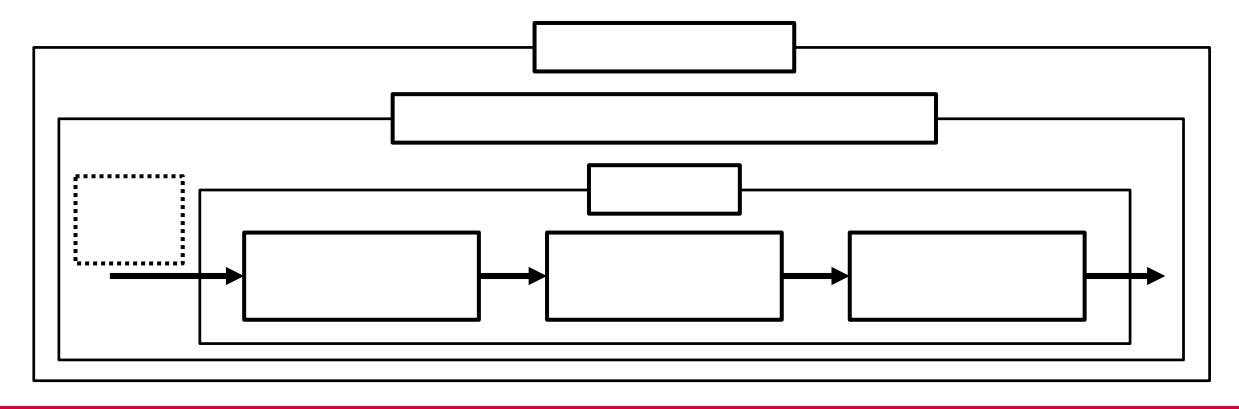
- How does the system get improved?
- What happens when something stop working well?













# Components of a Productive ML Sniff Test

- Surface-level understanding of some core ML concepts
- Sniff test procedure
  - Construct your mental picture of their overall approach
    - High-level ML system initial mental picture
    - Find the fuzzy-power words game to connect the story to the system
  - Dig deeper and refine the edges
- General tips

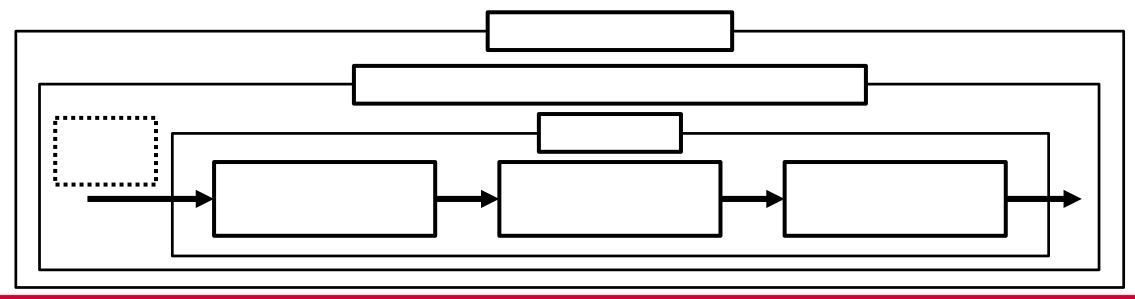


# Find the Fuzzy-Power Words Game

- Words/phrases that are said in a way say to convey of sense of
  - "The bullshitter doesn't care if what they say is true or false, but rather only cares whether or not their listener is persuaded"
- (For tech people) you've hit one if it's not clear how it is implementable in a computer
- Best way to articulate this is by example
- (Names and details have been changed to protect the innocent)



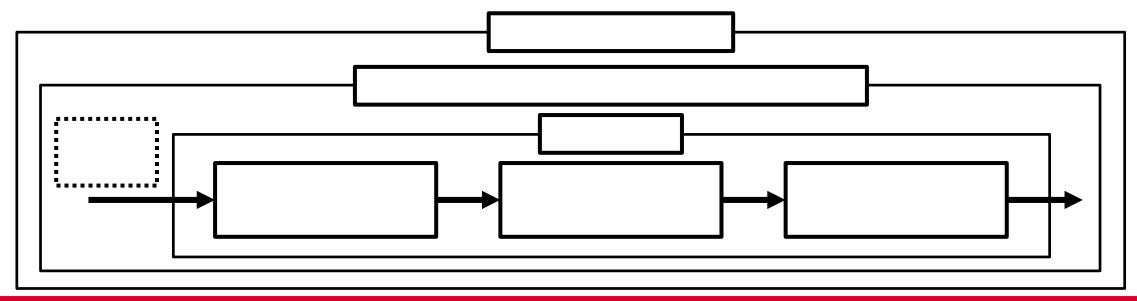








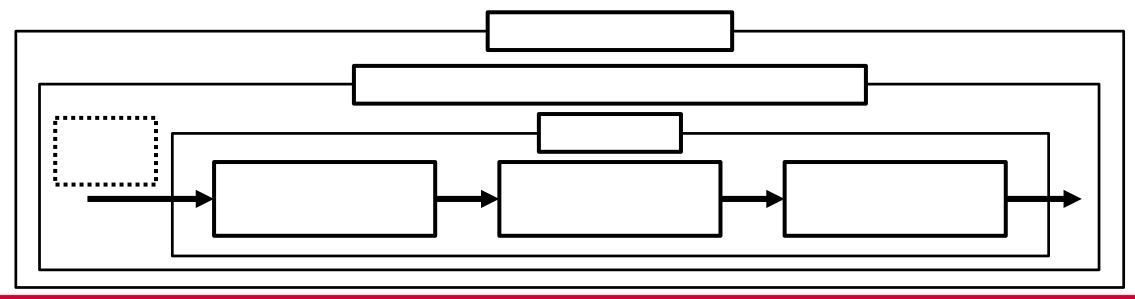
Al Trading through the Combination of the Wisdom of the Crowd and Expert Knowledge







Al rading through the Combination of the Wisdom of the Crowd and Expert Knowledge





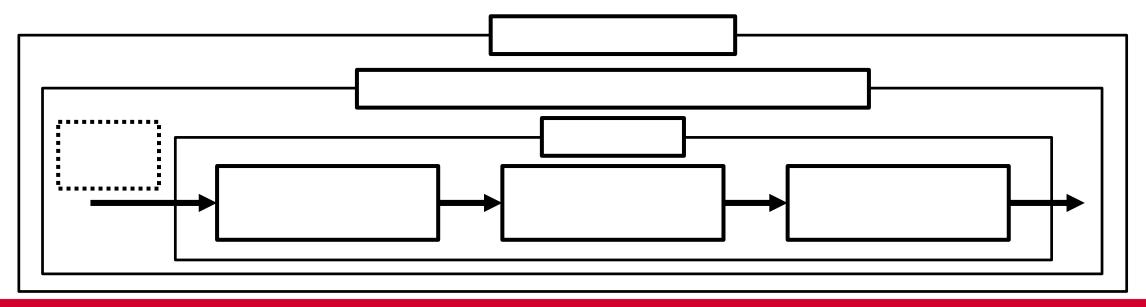


Al Trading through the Combination of the Wisdom of the Crowd and Expert Knowledge

Cutting edge analytics

Sentiment of social media

**Expert** insights







Al Trading through the Combination of the Wisdom of the Crowd and Expert Knowledge

**Cutting edge analytics** 

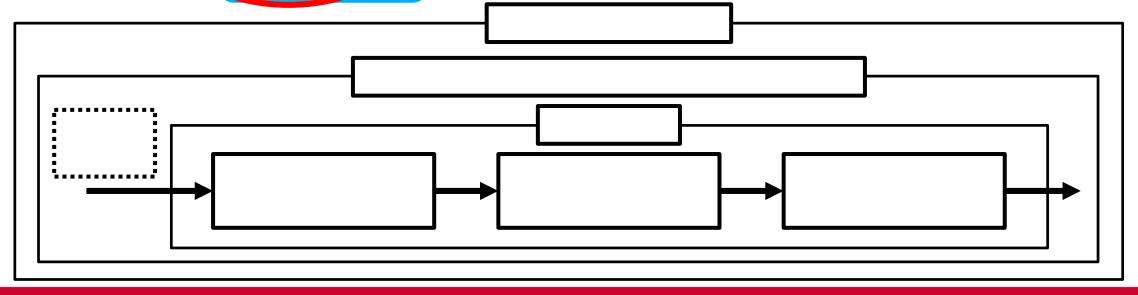
Sentiment of social media

**Expett** insights

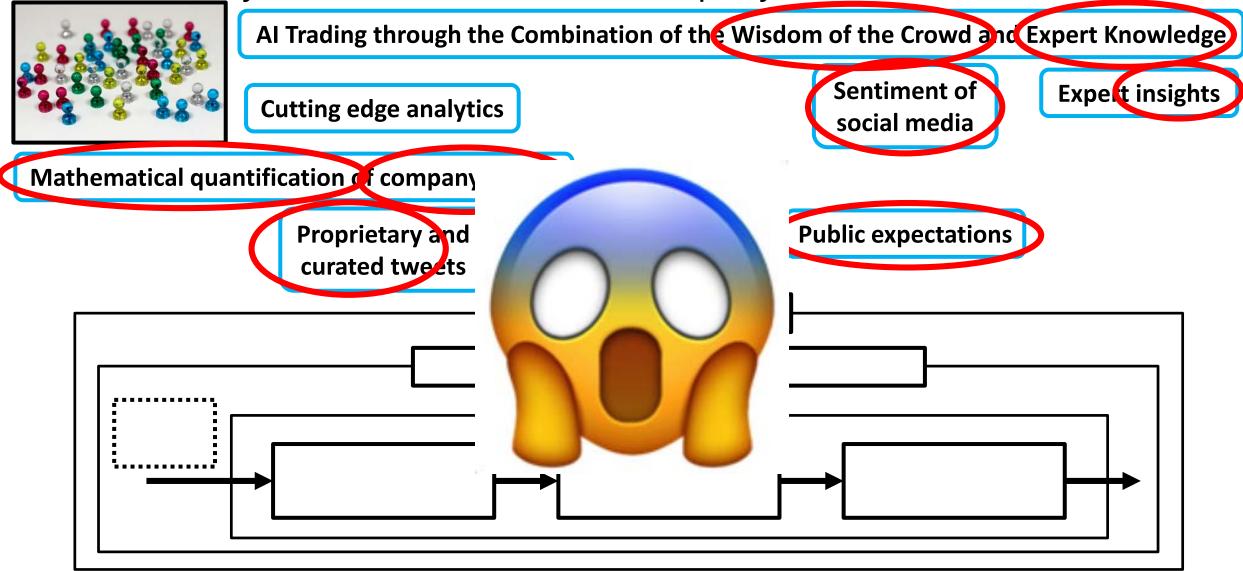
Mathematical quantification of company health

Proprietary and curated tweets

Public expectations











Al Trading through the Combination of the Wisdom of the Crowd and Expert Knowledge

**Cutting edge analytics** 

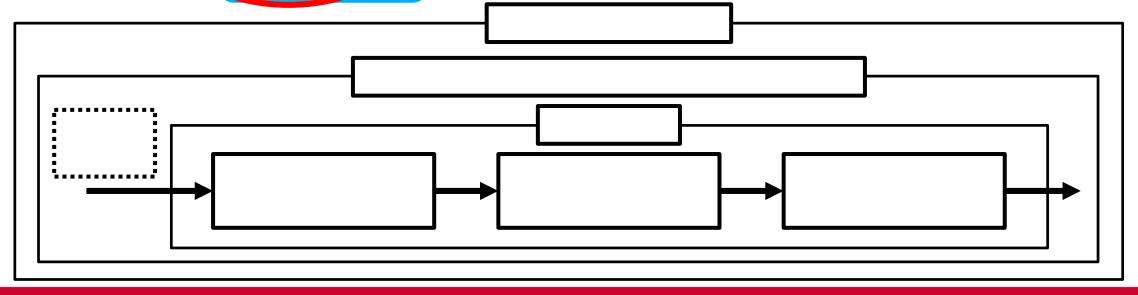
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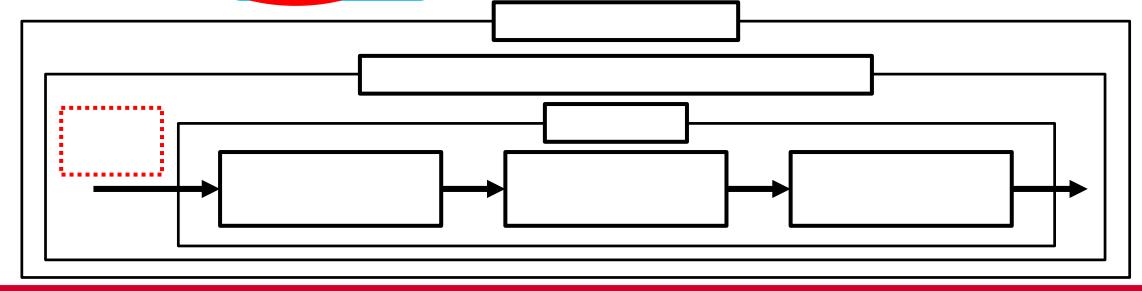
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Proprietary and curated tweets

Public expectations

Tweets from humanselected accounts





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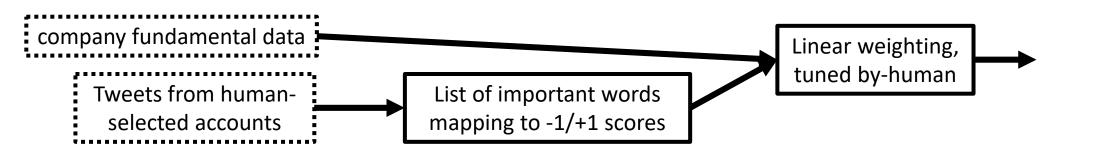
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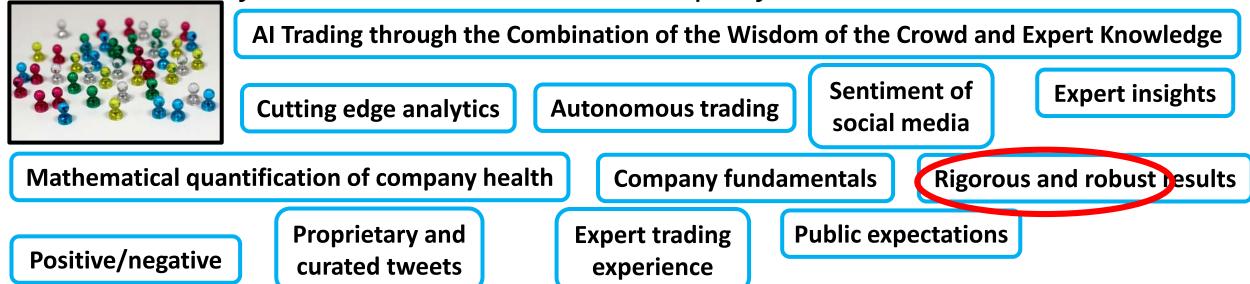
Positive/negative

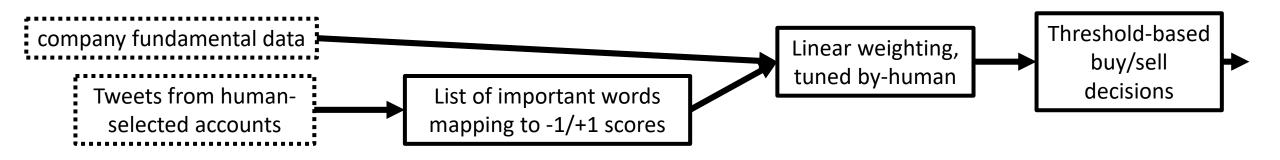
Proprietary and curated tweets

**Public expectations** 







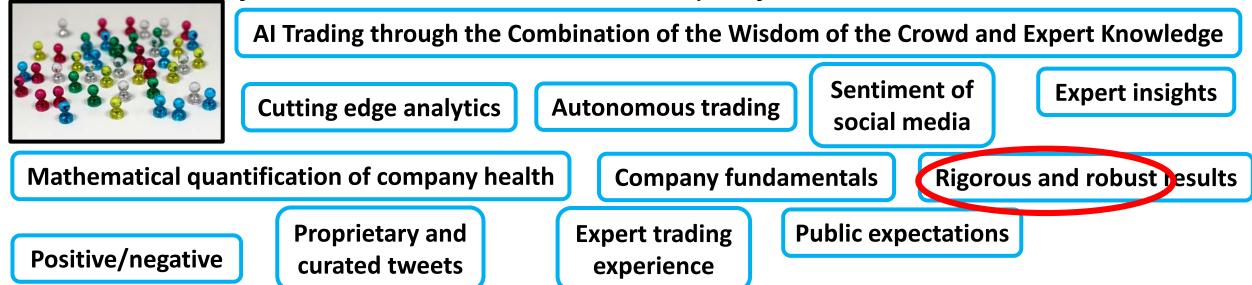


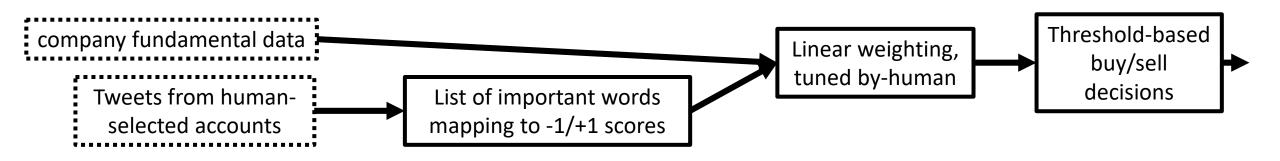


## Performance Testing: Red flags

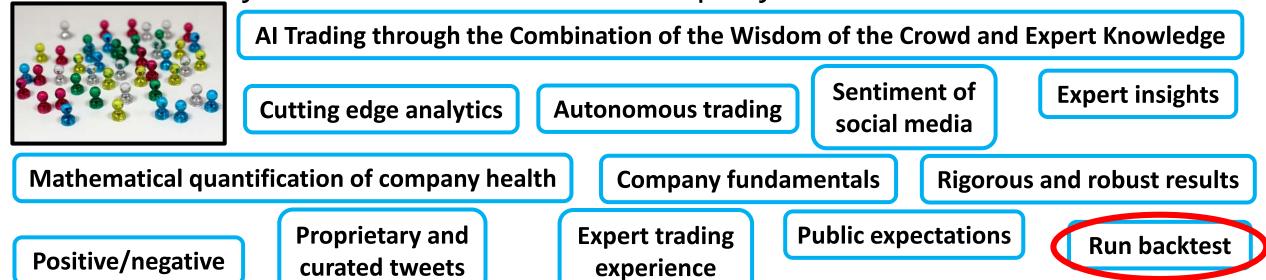
- They only show in-sample performance
  - (or don't clearly answer what is in-sample / out-of-sample)
- They don't have clear answers to expected future system performance with some understanding of the future performance's confidence
- They cite intuitive agreement as sufficient:
  - evidence of good future performance
  - justification for their methodology

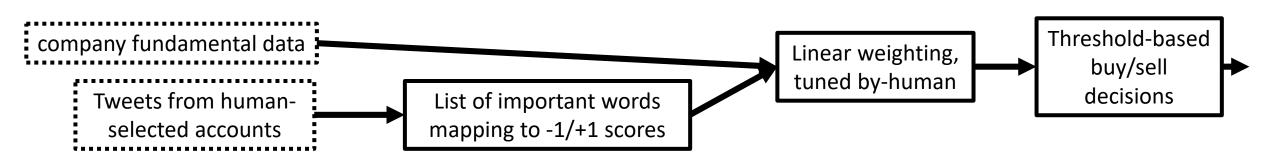








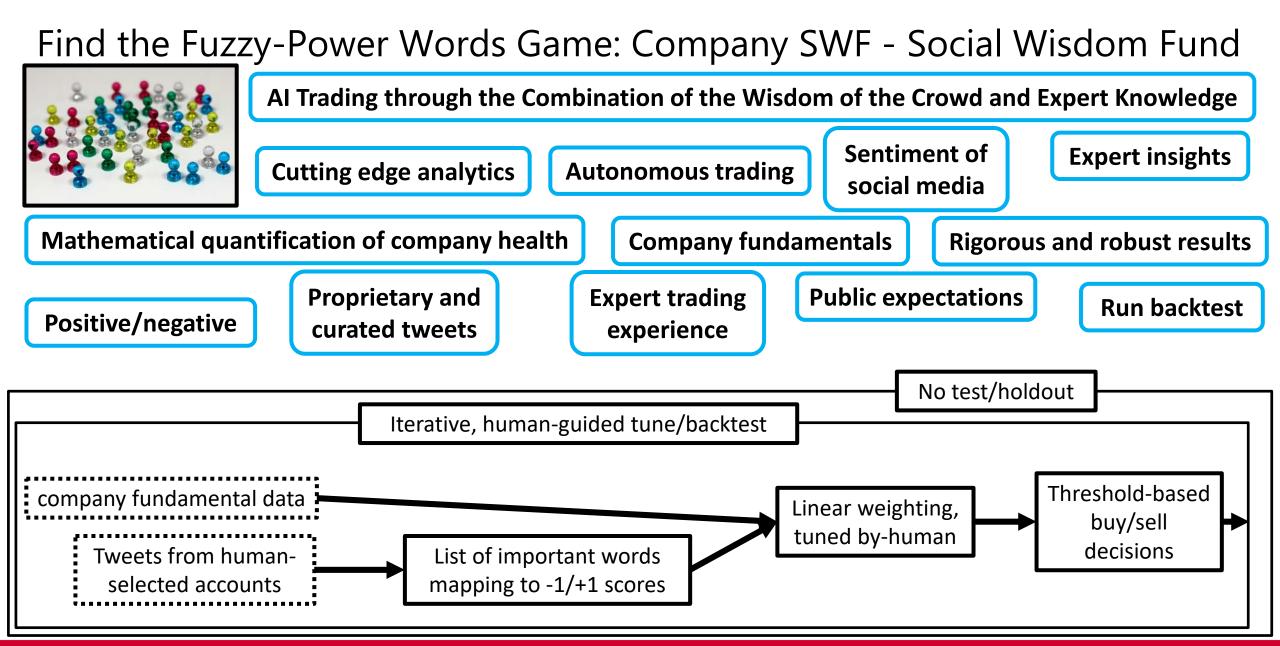


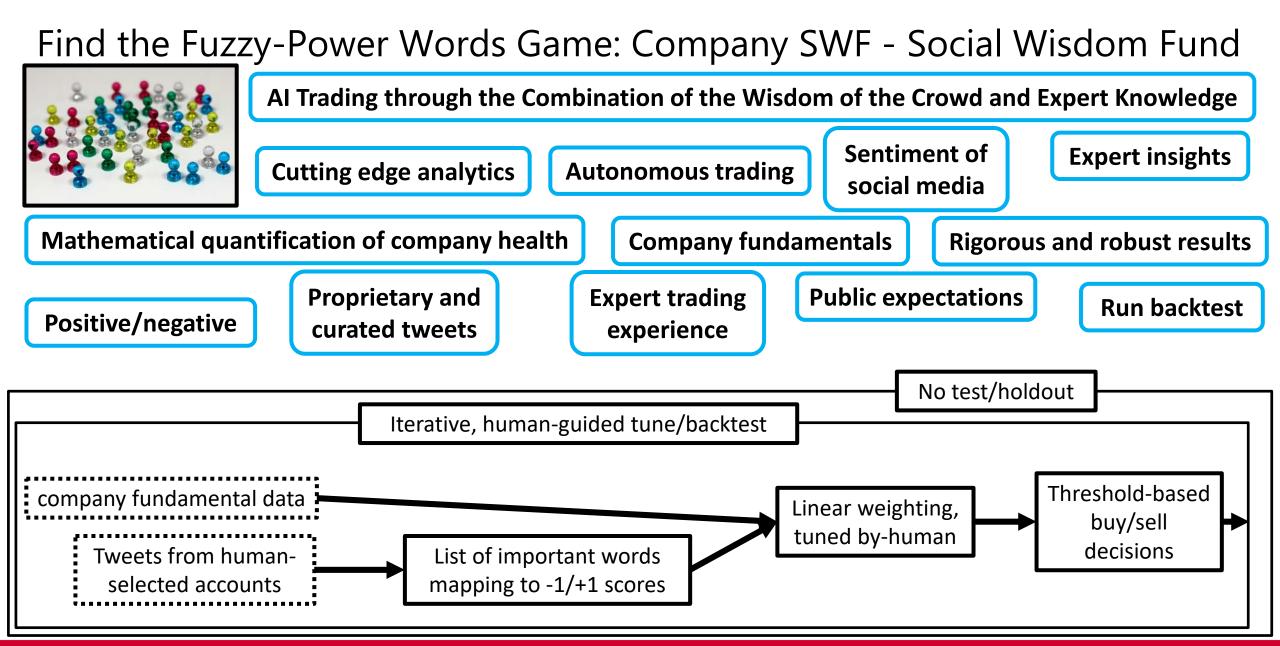


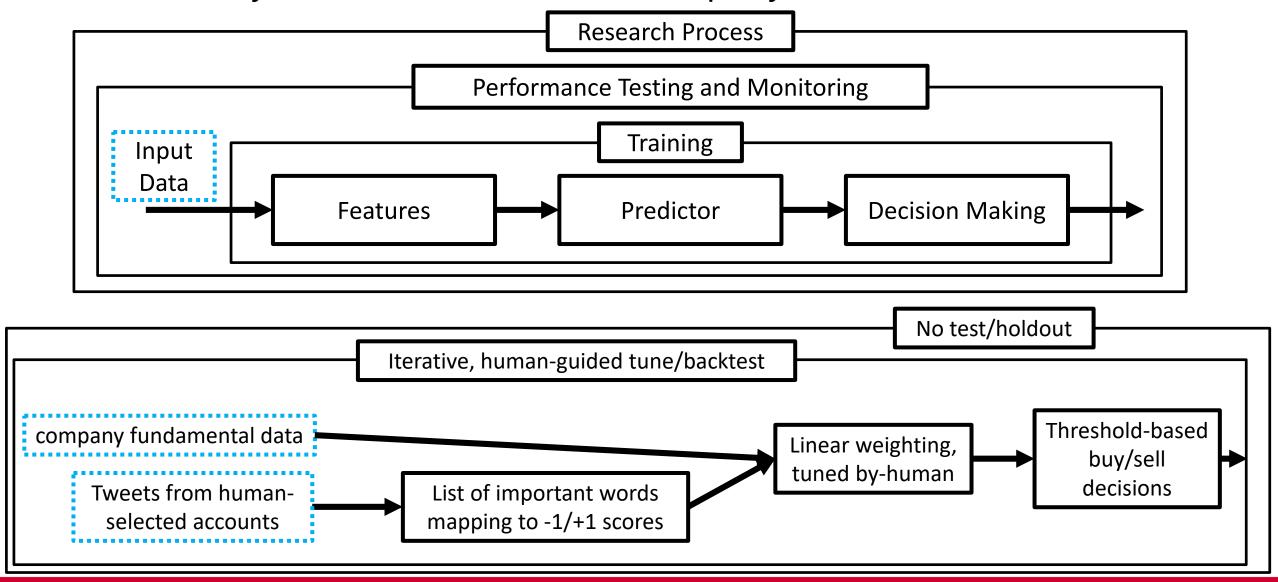


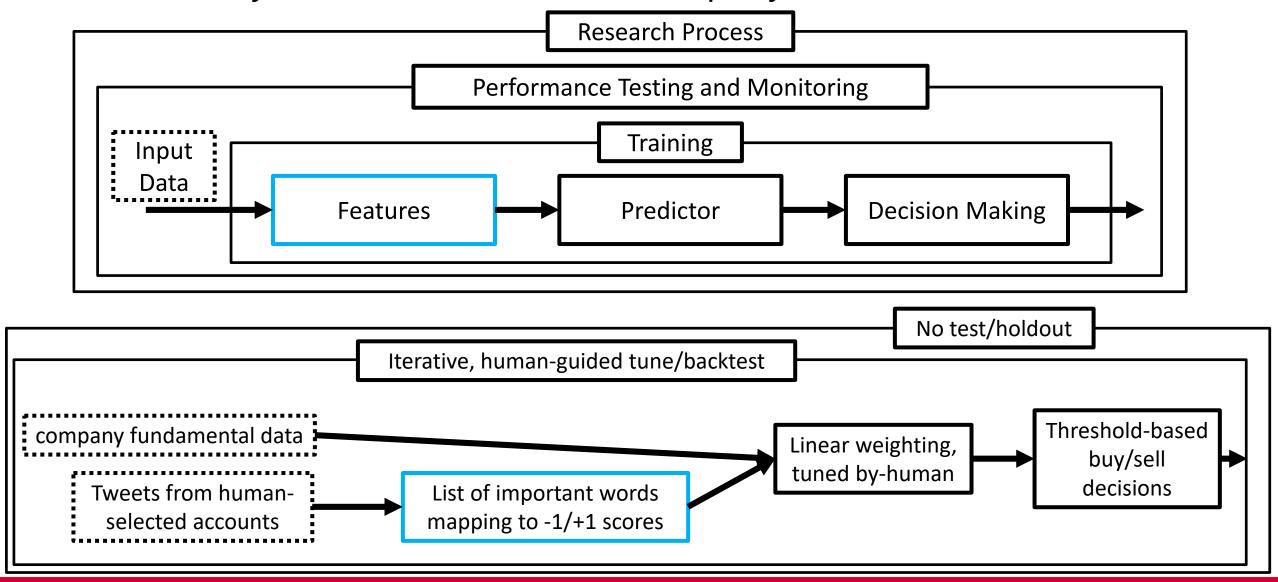
Find the Fuzzy-Power Words Game: Company SWF - Social Wisdom Fund Al Trading through the Combination of the Wisdom of the Crowd and Expert Knowledge Sentiment of **Expert insights Autonomous trading Cutting edge analytics** social media Mathematical quantification of company health **Company fundamentals Rigorous and robust results Proprietary and Expert trading Public expectations** Run backtest Positive/negative curated tweets experience Iterative, human-guided tune/backtest Threshold-based company fundamental data Linear weighting, buy/sell tuned by-human decisions Tweets from human-List of important words mapping to -1/+1 scores selected accounts

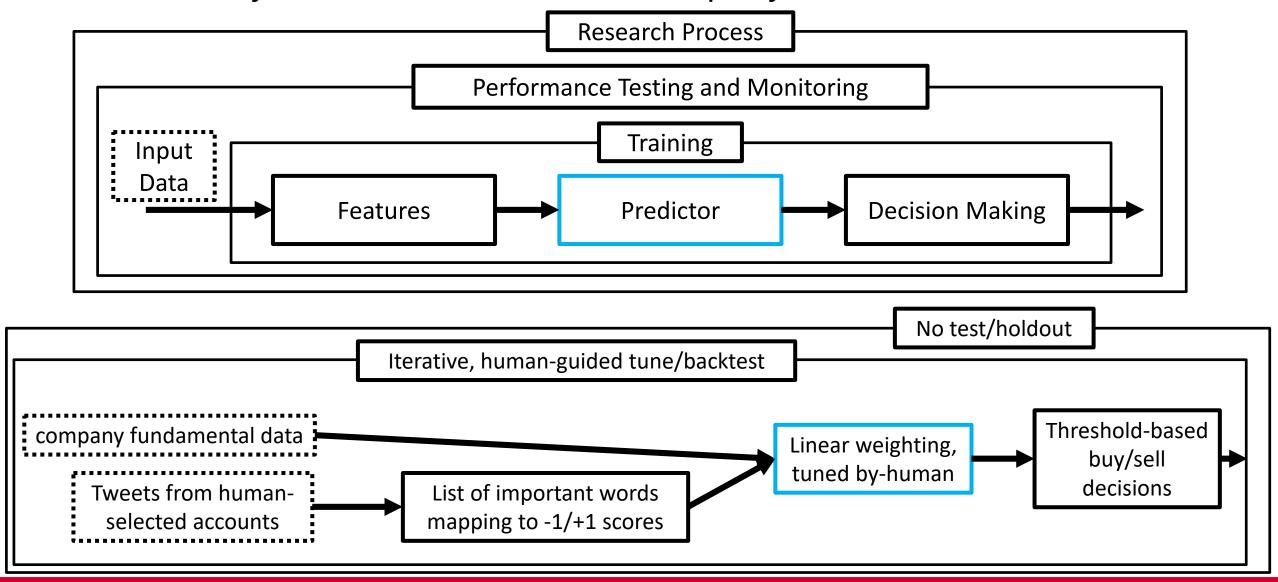


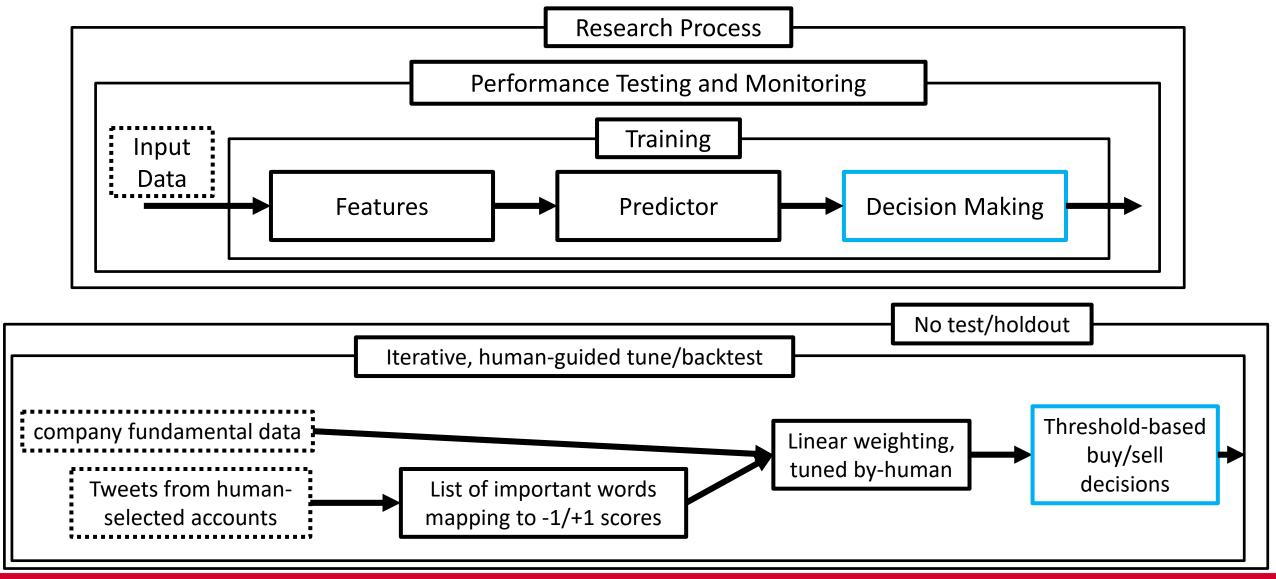


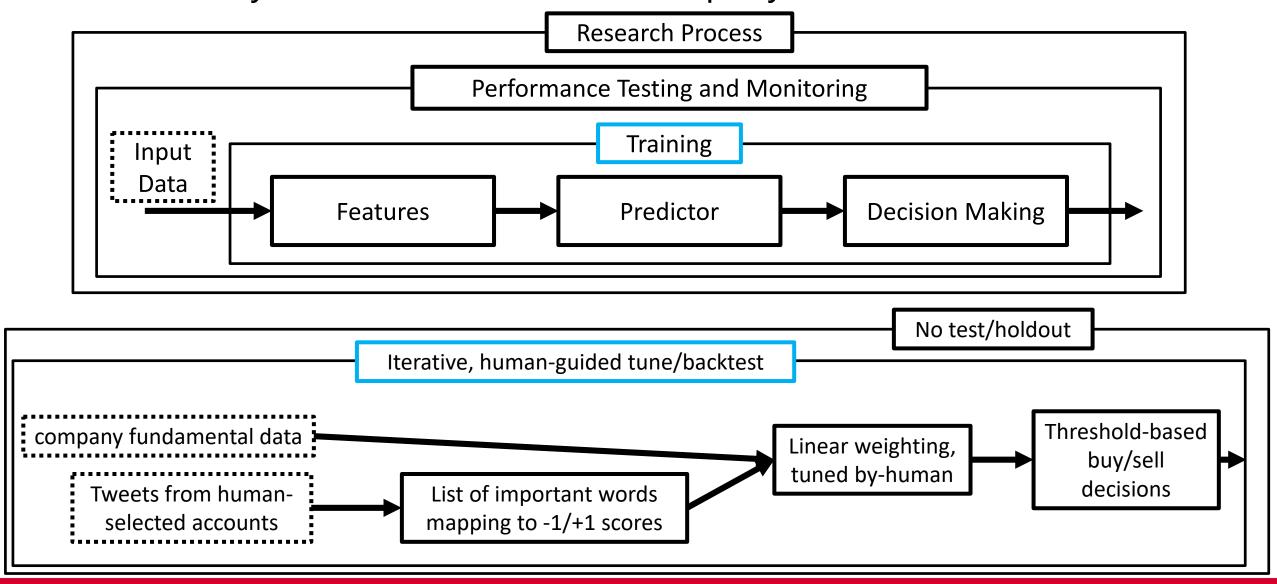


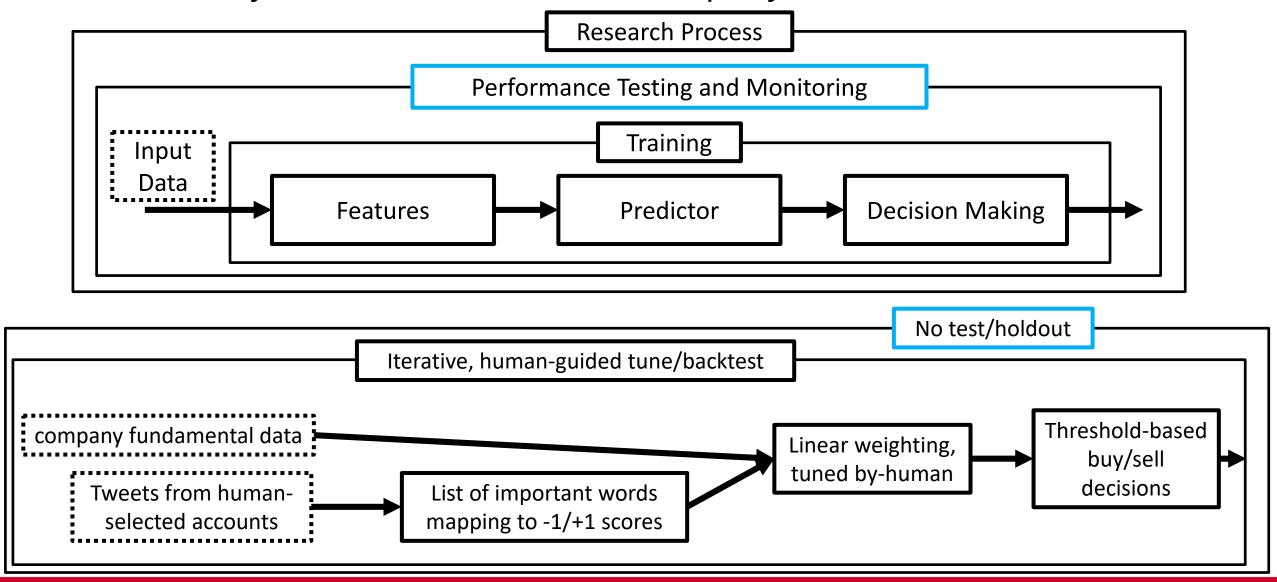


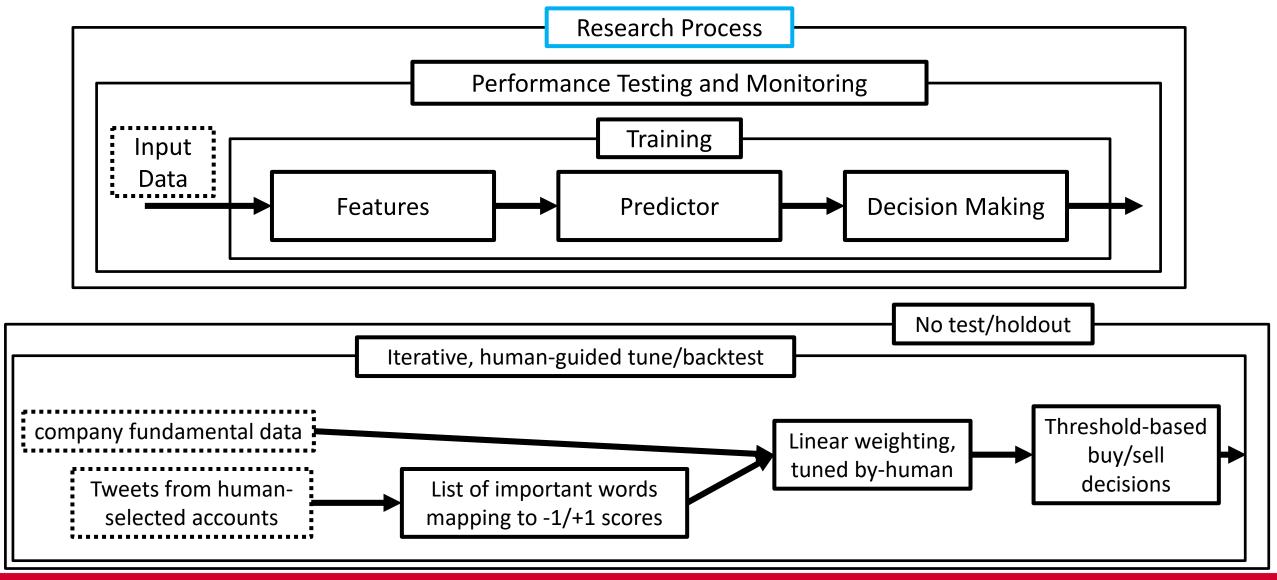












## Find the Fuzzy-Power Words Game: Company DCC – Deep Crypto Capital

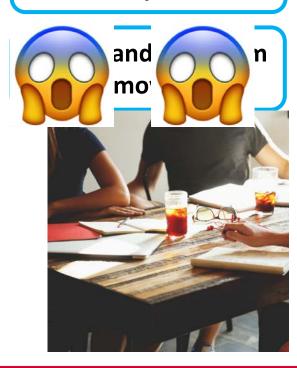
**Deep Learning of the Blockchain** Blockchains store the No human involvement – deep learning full transaction history discovers subtle patterns humans cannot see **Cryptocurrency** Its insight automatically selects The same technology that revolutionized market AI predictions what it believes has high conviction the IMAGENET competition **Bitcoin and Ethereum** We trade on the confidence of **Trained on specialized hardware** price movements price movements Compute performance on all the historical data GDAX historical Bitcoin Training on all historical data and Ethereum price and volume data Buy if predict it will go up with >90%, sell to fiat AlexNet 2016 if predict it will go down



## Find the Fuzzy-Power Words Game: Company DCC – Deep Crypto Capital

Blockchains store the full transaction history

**Cryptocurrency** market AI predictions



**Deep Learning of the Blockchain** 

No human involvement – deep learning discovers subtle patterns humans cannot see

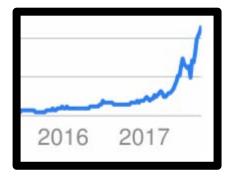


The same technology that revolutionized the IMAGENET competition

**Trained on specialized hardware** 

Its insight automatically selects what it believes has high conviction

We trade on the confidence of price movements





## High probability fuzzy-power words

- Algorithm
- Analytics
- Artificial intelligence
- Automatic
- Autonomous
- Big data
- Classification
- Cognitive \*
- Curated
- Data science
- Deep \*
- Descriptor
- Detect
- Enrich
- Expert
- Indicator

- Insight
- Machine learning
- Method
- Model
- Novel
- Platform
- Prediction
- Reasoning
- Robust
- Signal
- Statistical \*
- System
- Technique
- Technology
- Any human-like word
  - Thinks, knows, believes, understands, tries, etc.



## Components of a Productive ML Sniff Test

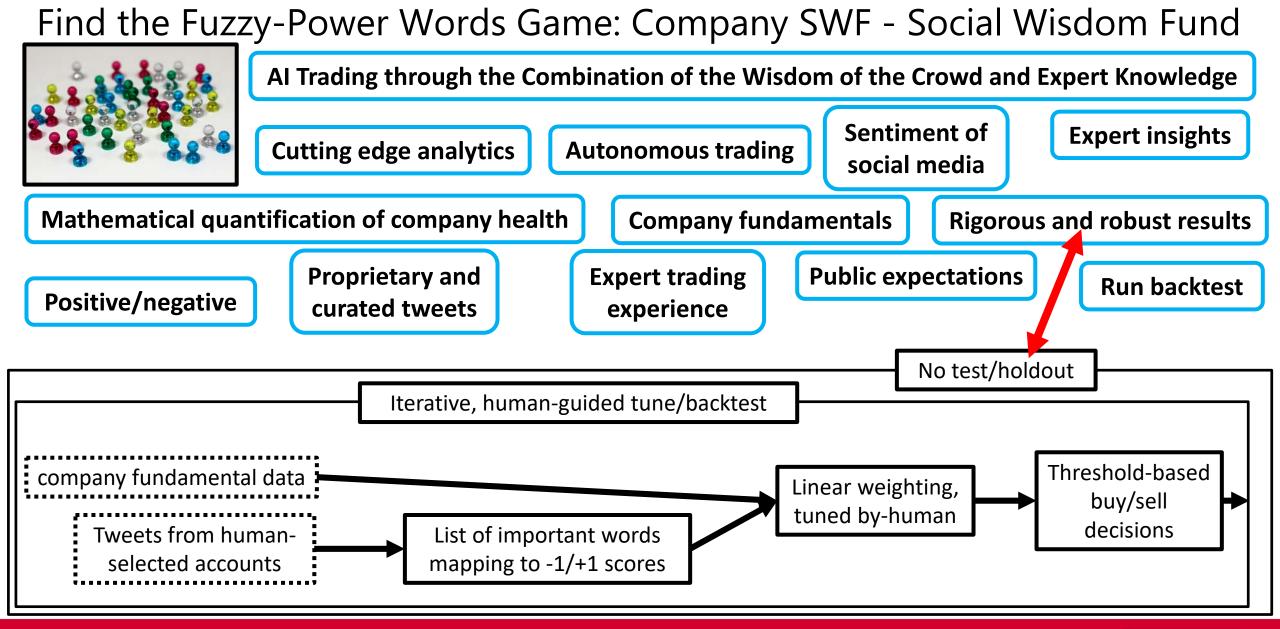
- Surface-level understanding of some core ML concepts
- Sniff test procedure
  - Construct your mental picture of their overall approach
    - High-level ML system initial mental picture
    - Find the fuzzy-power words game to build the full tree of how the story and system connects
  - Dig deeper
    - Probe into integrity gaps across hops
- General tips

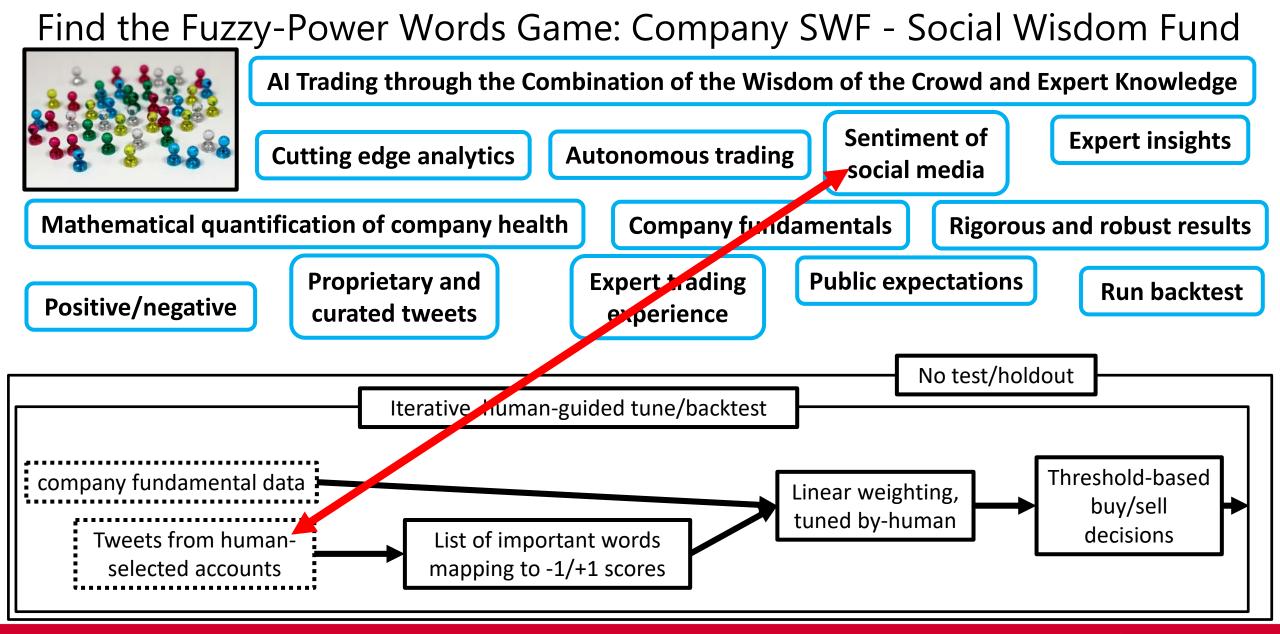


## Integrity Gaps Across Hops

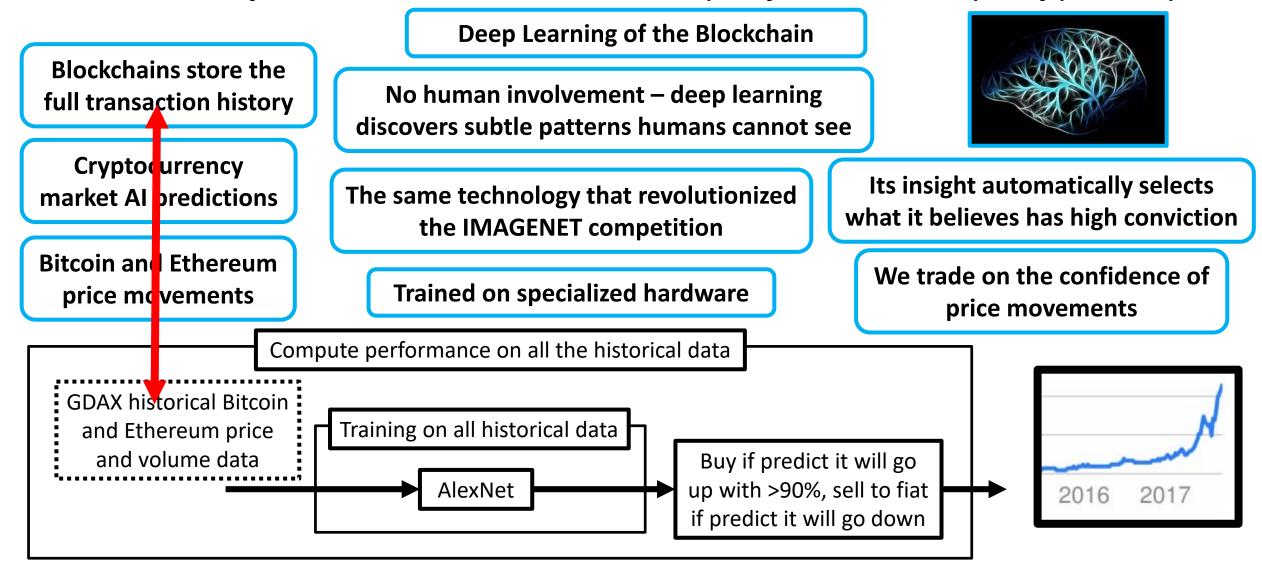
Now look back at the diagram, how much integrity is there in each hop?





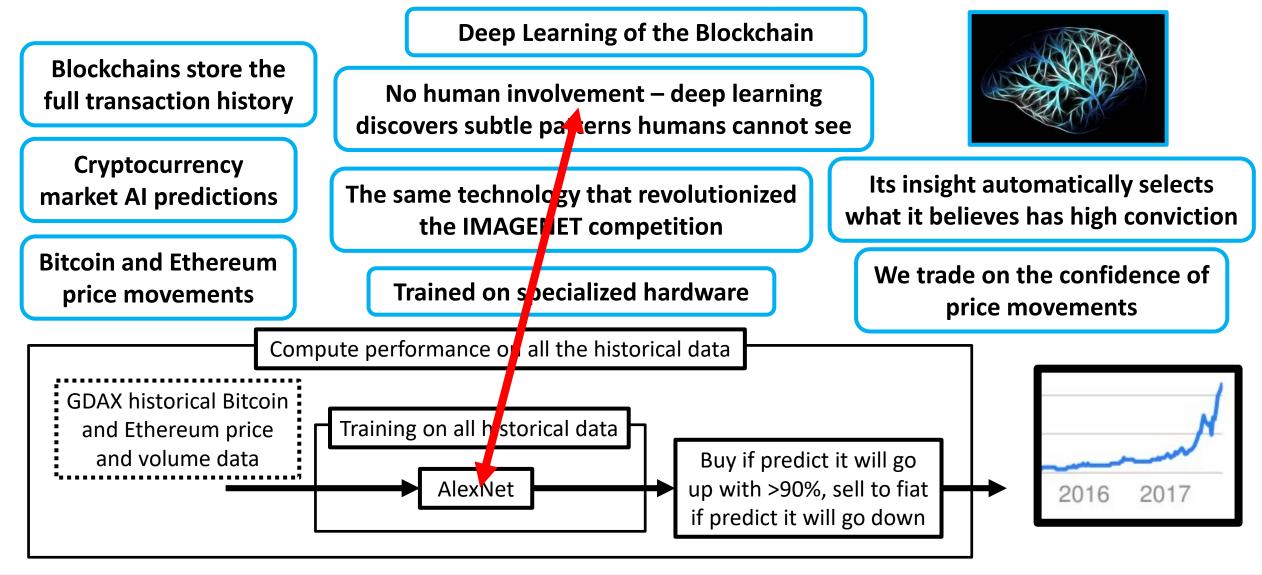


## Find the Fuzzy-Power Words Game: Company DCC – Deep Crypto Capital





## Find the Fuzzy-Power Words Game: Company DCC – Deep Crypto Capital





## **Integrity Gaps Across Hops**

- The purpose here is to discover if these "integrity gaps" are that:
  - They simplified it for our benefit
  - They don't view the gap as a gap and it's our misunderstanding
  - They are trying to deceive us



## Components of a Productive ML Sniff Test

- Surface-level understanding of some core ML concepts
- Sniff test procedure
  - Construct your mental picture of their overall approach
    - High-level ML system initial mental picture
    - Find the fuzzy-power words game to build the full tree of how the story and system connects
  - Dig deeper and refine the edges
    - Probe into integrity gaps across hops
    - Understand how well thought through each concrete box is with lists of questions
- General tips



## Lists of questions on each component of the system

#### \* Where does the data come from? \* How much history do you have? \* What is the resolution of your data? \* Are there any large gaps or outages in your data? \* What kind of sanity checking, cleaning, and outlier detection/removal do you do?

- \* How do you check for changes in the data format? How many times has that happened? \* What is the biggest source of noise in the data?
- \* Who else has access to the same data?
- \* Has anyone used data like yours to solve a problem like yours?
- \* How much "human curation" is in your data?
- \* What filtering is in place?
- \* How is the data stored?
- \* Are there sporadic performance-effecting latencies in your data arrival?
- \* Can you give me specific examples of what your data actually is?

- \* How do you represent features in your system?
- \* How often do you add/change/remove features?
- \* Can you give me three concrete examples of features that are currently live in your system? \* How do you actually perform the fitting/learning/search/optimization?
- \* How much human domain knowledge is imbedded in your features?
- \* Do you normalize/transform your features somehow?
- \* How do you handle heterogenous data sources?
- \* Roughly, how many features do you use?
- \* (If feature selection, dimensionality reduction, etc. methods are used)
- \* Why were these methods chosen?
- \* What effect do they have on the system's overall performance?
- \* Why do these features make sense for the decisions you want to make?

- \* What is the meaning of the prediction output?
- \* What type of representation do you use to go from features to a prediction?
- \* On what timescales is your system outputting predictions?
- \* How does your system quantify its uncertainty in a prediction?
- \* Why did you chose that representation from the many, many of other methods?
- \* What alternate methods did you try? Why were those passed on?
- \* How much human domain knowledge is imbedded in your prediction representation?
- \* What are other successful applications of your chosen representation?
- \* Why does your predictor representation make sense for the decisions you want to make?
- \* If more than one predictor (for example, using ensembles):
- \* Roughly how many models do you use?
- \* Do you find most of your performance comes from a few of the models?
- \* How do you validate that you increase performance by adding additional models?

#### Decision making:

- \* What is the meaning of the decisions you are making?
- \* On what timescales is your system outputting decisions?
- \* What type of representation do you use to go from a prediction to a decision?
- \* What alternate methods did you try? Why were those passed on?
- \* How much human domain knowledge is imbedded in your decision making representation?
- \* How does your system quantify its uncertainty in a prediction?
- \* Why does your decision making representation make sense for the decisions you want to make?

#### Training:

- \* What parts of your system "learn" from data?
- \* Where do your labels come from? How accurate are they?
- \* How much human domain knowledge is in the fitting process?
- \* What is the rough ratio of (# data points)/(# features)?
- \* Do you believe there is systematic noise in your data somehow? How do you correct for it?

  \* What objective function do you use? Why? How did it come about? How much tuning was
  - \* Roughly what order of magnitude of parameters are you fitting?
  - \* What are alterative objective functions you have tried?

  - \* What alternative optimization techniques have you previously tried? Why were those
  - \* How do you understand if your system is overfitting/underfitting?
  - \* How often do you re-fit your representations? How much does that increase your performance?

#### Performance testing:

- \* How do you test the performance of your overall system?
- \* How do you test the performance of single components of your system (e.g., the decision
- \* Exactly how large is your train/test/holdout sets? How are they kept separate?
- \* What assumptions is your overall approach making? How have you validated these assumptions
- \* What are the metrics you use to measure performance across your system?
- \* What is your overall performance? With confidences.
- \* How do common baseline methods perform on your problem? With performance and confidences.
- \* Do you explicitly regularize or measure/control the complexity your representation somehow? \* Can you explain a couple situations of both unexpectedly high and low performance?
  - \* What do you believe is the maximum achievable performance? Why?
  - \* How have the dynamics of your data/problem changed over time?
  - \* How much do your estimated and live performances differ? What are the sources of these
  - differences? How do you represent and compensate for them?
  - \* Do you validate against simulated data where you know your assumptions hold? How is the simulated data generated?
  - \* Does your performance make intuitive sense to you? Why or why not?

#### Monitoring for performance changes:

- \* How are you monitoring for performance changes?
- \* How often do you expect to detect changes in performance?
- \* Do you have methods for early-detection of performance changes for each individual
- component before it shows up in overall performance?
- \* When has your monitoring caught a change in performance?
- \* How do you think about the difference between an anomalous environmental condition and a change in performance?

#### Research process:

- \* Describe your overall research philosophy
- \* For any change that is made to the overall system (method, implementation, etc), what is the process that validate and approves the change?
- \* How often is the methodology or a component of the system changed?
- \* Who has access to the entire data set? What policies are in place to prevent data snooping?
- \* What change made it through your validation process that turned out to decrease performance? Why did that happen? How was your process changed to prevent this from happening
- again in the future? \* What is the likely next research piece to make it into production?
- \* What roles comprise your research team? Why?
- \* How do you allocate time across your team?
- \* What part of your system keeps you up at night? Why?
- \* What has worked much better/worse than you had expected?
- \* How is your live system influencing/corrupting your future data? How are you correcting for
- \* What other data sources have you investigated?
- \* How closely does your in-sample data represent your out-of-sample?

# github.com/alpha-features/oreilly-sf-ai-conference-2017/

(Don't worry, you don't have to read it all. It's there so you have lists of questions for later.)



## Components of a Productive ML Sniff Test

- Surface-level understanding of some core ML concepts
- Sniff test procedure
  - Construct your mental picture of their overall approach
    - High-level ML system initial mental picture
    - Find the fuzzy-power words game to build the full tree of how the story and system connects
  - Dig deeper and refine the edges
    - Probe into integrity gaps across hops
    - Understand how well thought through each concrete box is with lists of questions

#### General tips

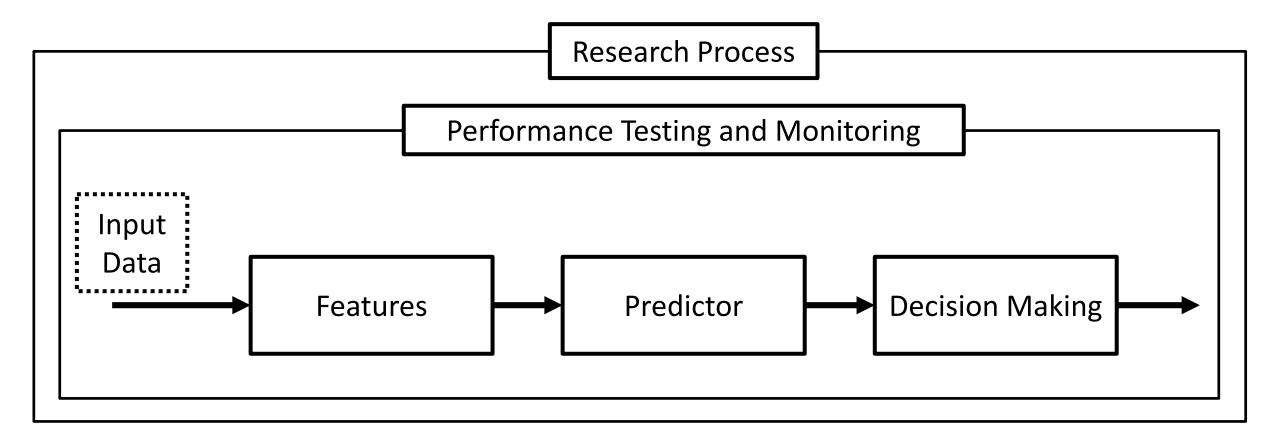


## General Tips

- Tricks to pull out in the meeting
  - Purposefully ask a wrong question 1 out of 5 times (super-power)
  - Jump on strangely out of place, overly precise jargon
- Helpful mindsets
  - You are on the easy side of the table (burden of proof is on the seller)
  - We are uninterested in inferring whether anyone is smart or stupid
    - At worst, their story and methodology gives us no information about their future performance



## What about an AI system?





# Josh, I feel like I'm still missing half the story here...

A Practical Guide to Conducting an AI Snake Oil Sniff Test

Understanding what they're doing

**Evaluation of what they're doing** 

**Understanding of ML core concepts** 

Sniff test procedure

General tips

Some niche benchmarks

Run a trial

It's the "best" one based on ad-hoc qualities

Initial ML system mental picture

Find the fuzzy-power words

Integrity gaps

Lists of questions

Benchmarks that industries care about

AI/ML best practices (by industry?)

Detailed success/failure case studies

github.com/alpha-features/oreilly-sf-ai-conference-2017/

Why do they think this works and do we agree with their thinking?

