O'REILLY" Artificial

A Practical Guide to Conducting an Al Snake Oil Sniff Test

Josh Joseph

Chief Science Officer, Alpha Features

jj@alphafeatures.com

Intelligence

oreillyAlcon.com **#OReillyAI**







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



Expert insights

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



Cutting edge analytics



Expert insights

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



Sentiment over social media

Cutting edge analytics



Rigorous and robust results

Expert insights

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



Sentiment over social media

Cutting edge analytics



Analytics? Isn't it just averaging?

Rigorous and robust results

Expert insights

Are our internal results not robust?

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



Sentiment over social media

Cutting edge analytics



Analytics? Isn't it just averaging?

Most of the "crowds"
I know are idiots

How is this Artificial Intelligence?

Are our internal results not robust?

0

Rigorous and robust results

Expert insights

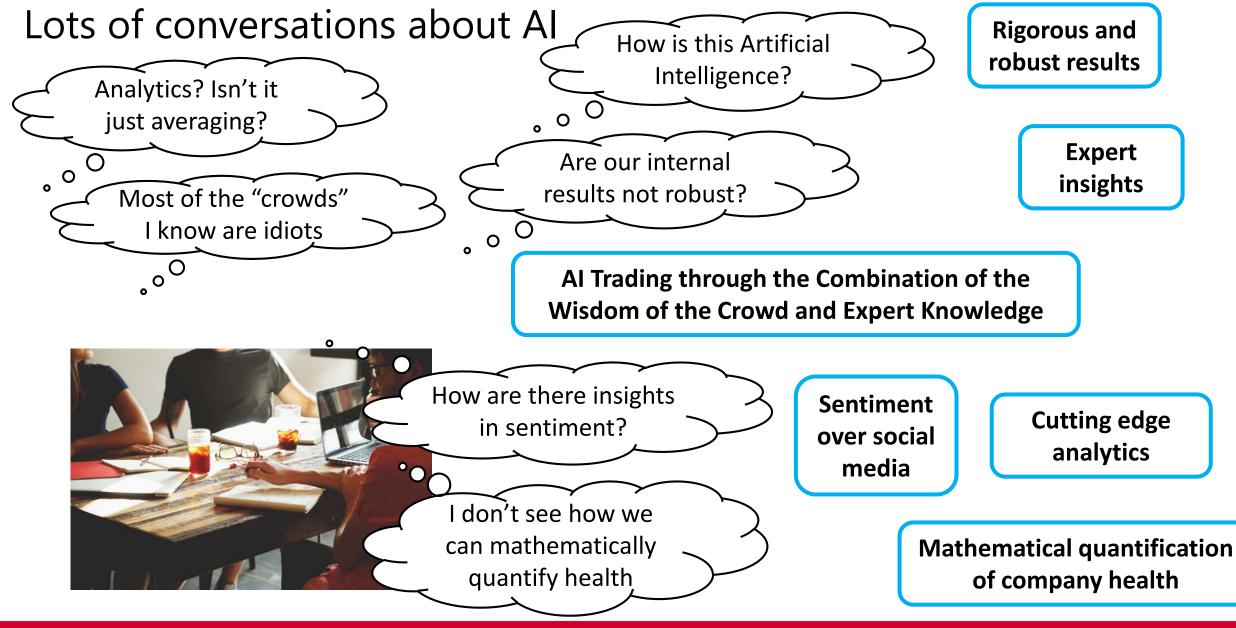
Al Trading through the Combination of the Wisdom of the Crowd and Expert Knowledge

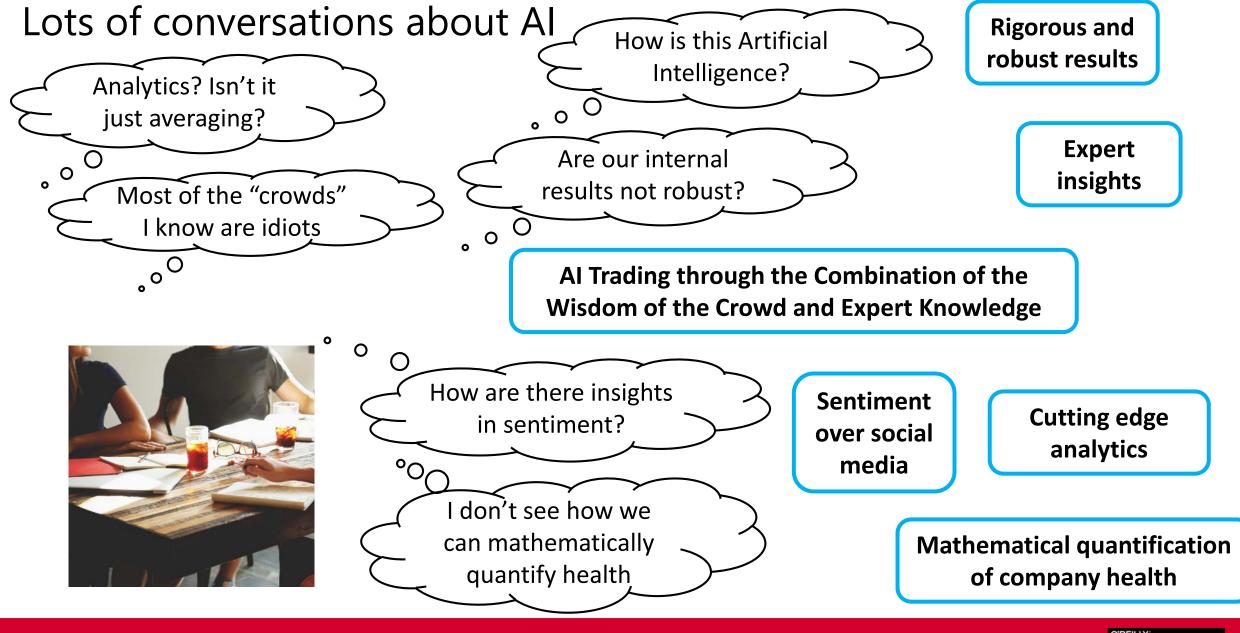


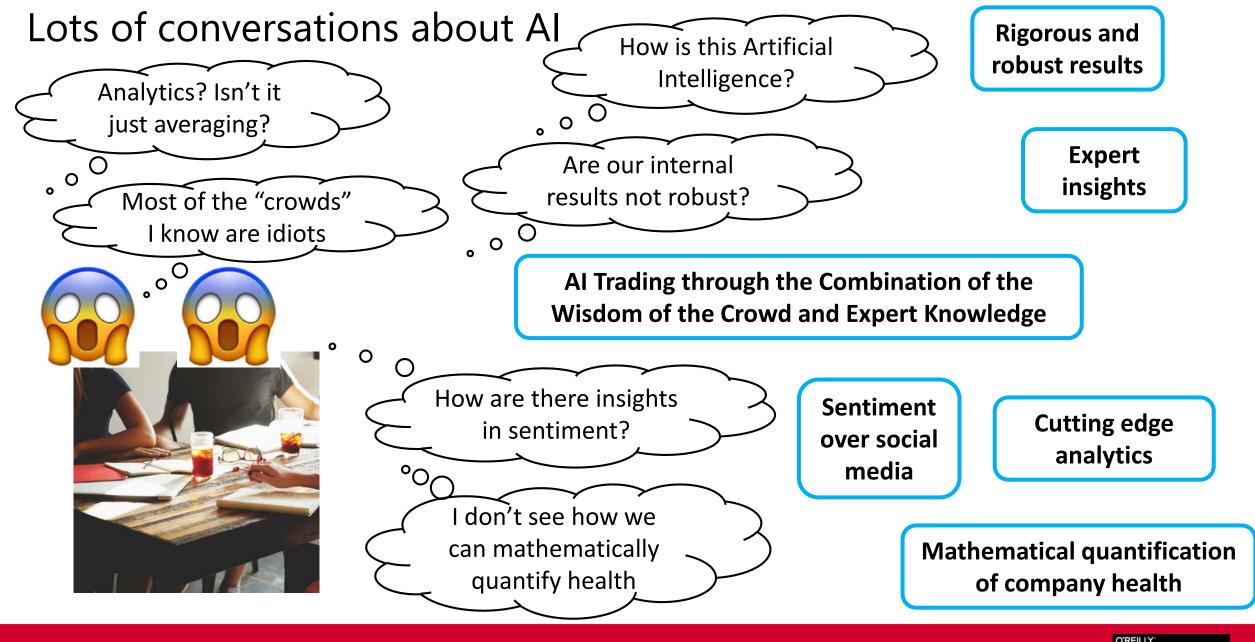
Sentiment over social media

Cutting edge analytics









Rigorous and robust results

Expert insights

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



Sentiment over social media

Cutting edge analytics



Smart team!

Rigorous and robust results

Expert insights

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



Sentiment over social media

Cutting edge analytics



Awesome they have machine learning in the cloud!

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



Sentiment over social media

Cutting edge analytics



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!

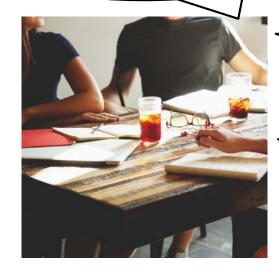
Sentiment over social media

Cutting edge analytics



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>



Awesome they have machine learning in the cloud!

Joe was just talking about how random forests are super cool



Smart team!

What th

An Of

<Insert super important
business decision being made>

Rigorous and robust results

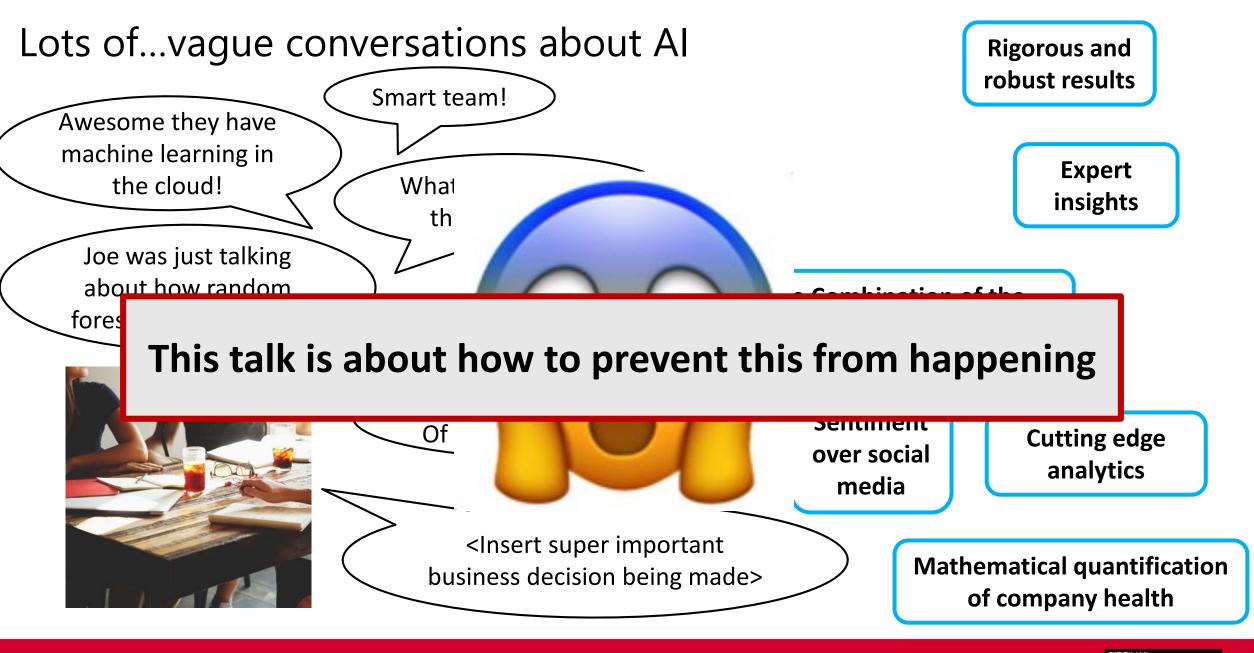
Expert insights

e Combination of the and Expert Knowledge

Sentiment over social media

Cutting edge analytics

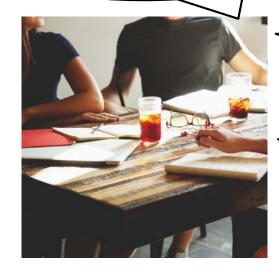






Awesome they have machine learning in the cloud!

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>



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

 \equiv

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)

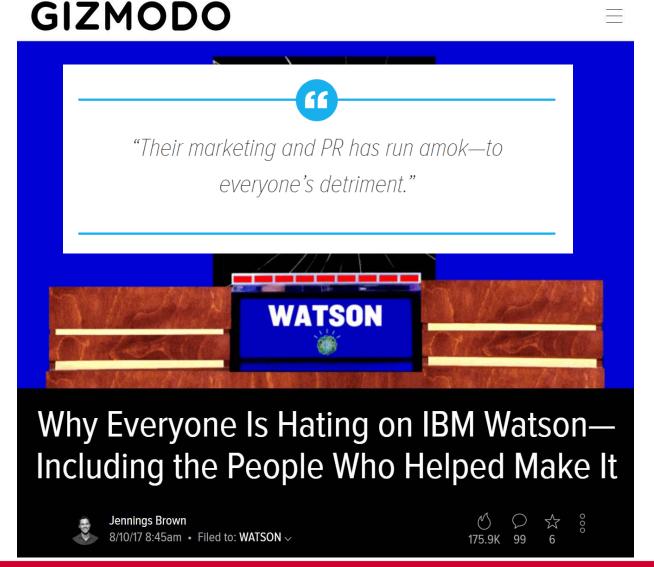
Creating Shareholder Value with AI? Not so Elementary, My Dear Watson

Key Takeaway

Our checks suggest that while IBM offers one of the more mature cognitive computing platforms today, the hefty services component of many AI deployments will be a hindrance to adoption. We also believe IBM appears outgunned in the war for AI 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

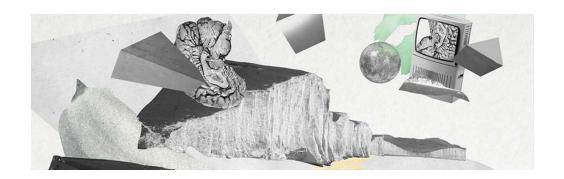
By LUKE DORMEHL

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.

Many, many experiences like 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
- Due diligence on over a hundred AI/ML hedge funds



Many, many experiences like 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
- Due diligence on over a hundred AI/ML hedge funds

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





Many, many experiences like 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
- Due diligence on over a hundred AI/ML hedge funds

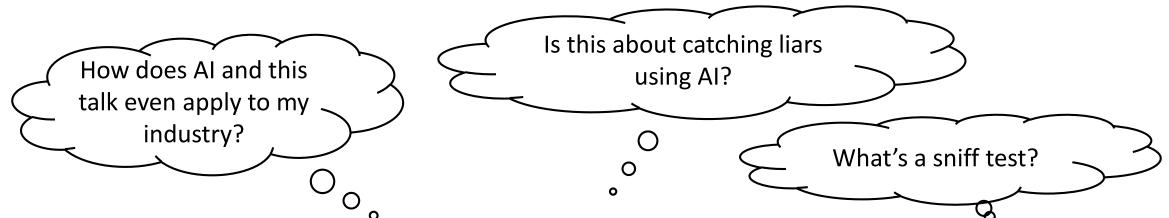
...so you can imagine there's been a *lot* of



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

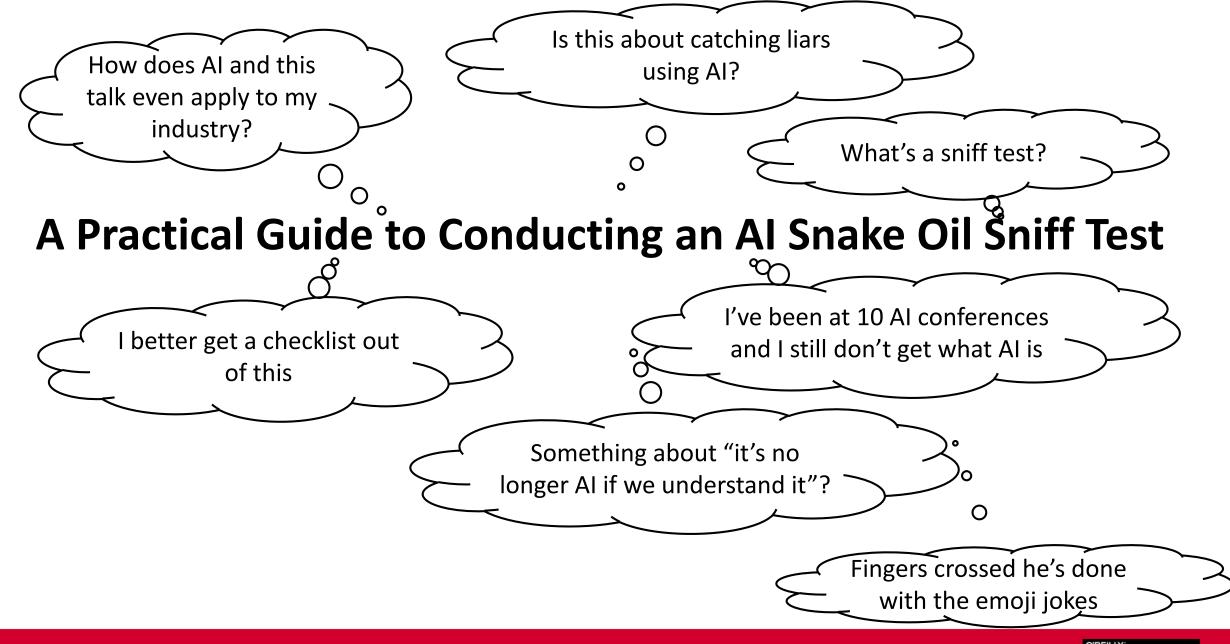










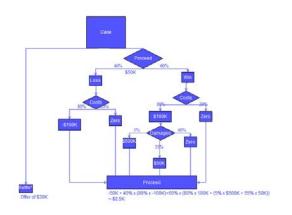


A hodgepodge of rules discovered somehow (that can be implemented in a computer)

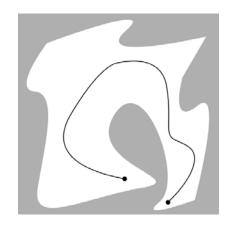


An amalgamation of rules discovered somehow (that can be implemented in a computer)



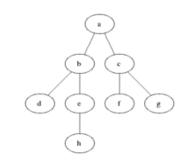


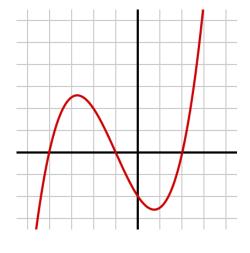
```
If (boolean condition) Then
     (consequent)
Else
     (alternative)
End If
```



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

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

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

30 minute to 2 hour meeting

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)





concrete process, questions, tips

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

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)

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



Components of a Productive ML Sniff Test

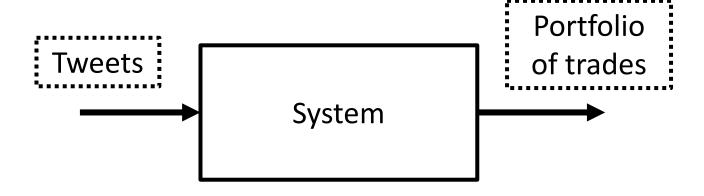
- Surface-level understanding of some core ML concepts
- Sniff test procedure
- General tips



- Generalization
 - How will my system perform when I turn it on?
 - To the future, changing environment, new users, additional markets, different geographies, etc.



- Generalization
 - How will my system perform when I turn it on?
 - To the future, changing environment, new users, additional markets, different geographies, etc.





- Generalization
 - How will my system perform when I turn it on?
 - To the future, changing environment, new users, additional markets, different geographies, etc.
- No such thing as zero human involvement



- Generalization
 - How will my system perform when I turn it on?
 - To the future, changing environment, new users, additional markets, different geographies, etc.
- No such thing as zero human involvement
- Predictive power can only come from either information in the data or information a human encoded



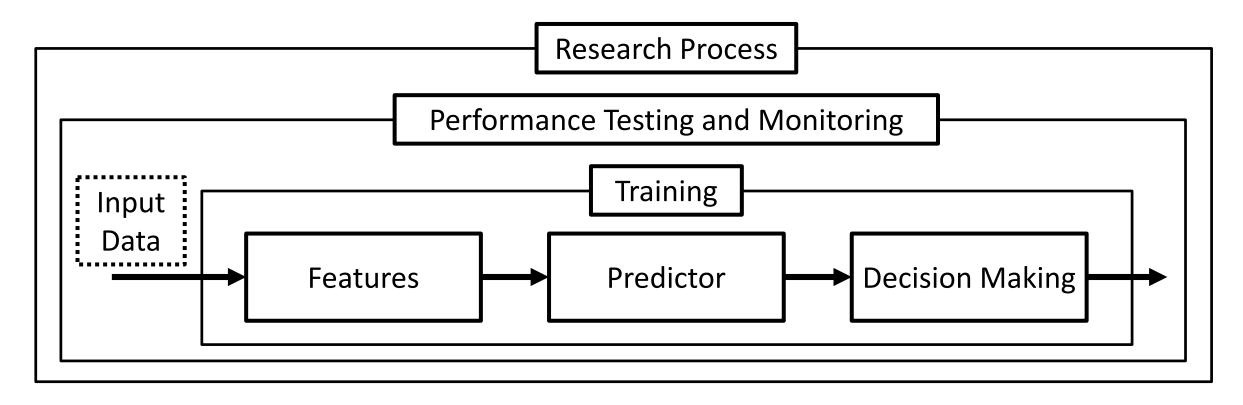
- Generalization
 - How will my system perform when I turn it on?
 - To the future, changing environment, new users, additional markets, different geographies, etc.
- No such thing as zero human involvement
- Predictive power can only come from either information in the data or information a human encoded
- The amalgamation of rules inside these systems make assumptions
 - Not knowing the assumptions you're making is gambling



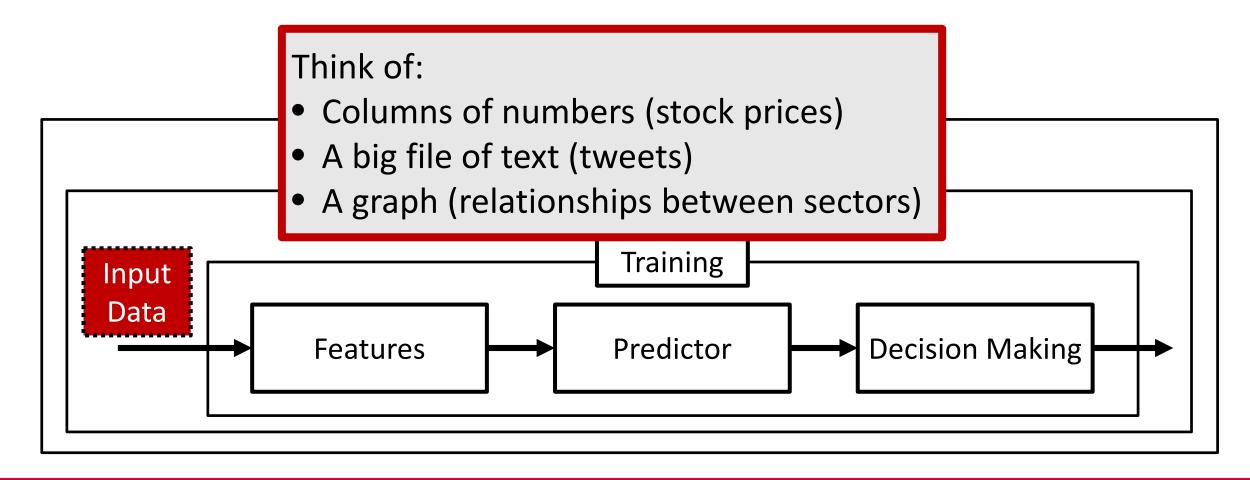
Components of a Productive ML Sniff Test

- Surface-level understanding of some core ML concepts
- Sniff test procedure
 - Construct your mental picture of their overall approach
 - Dig deeper and refine the edges
- General tips

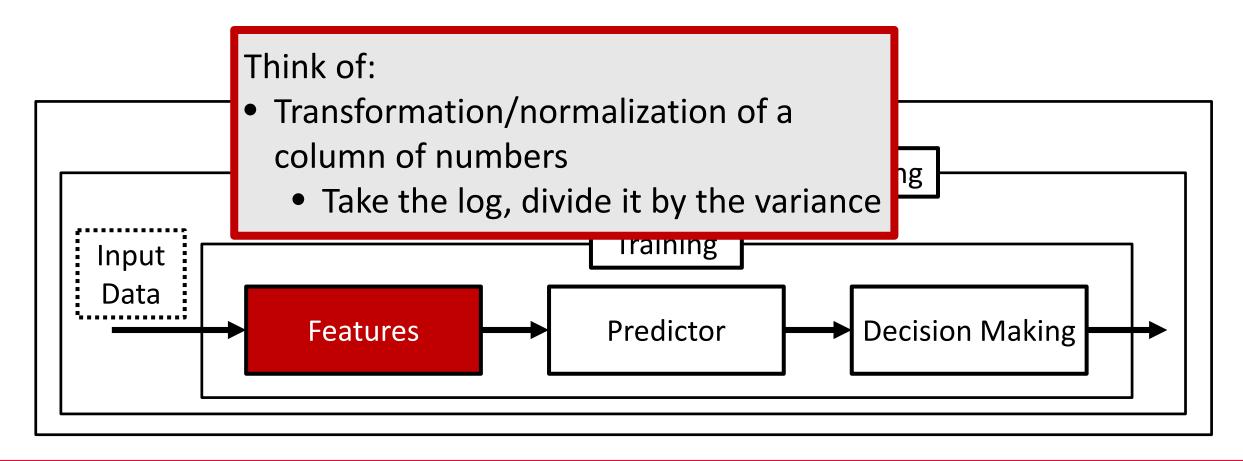


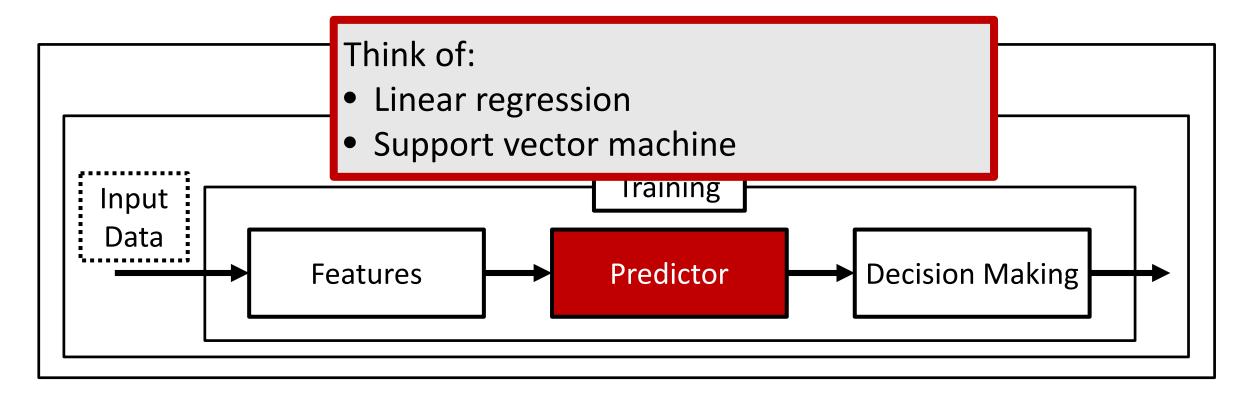




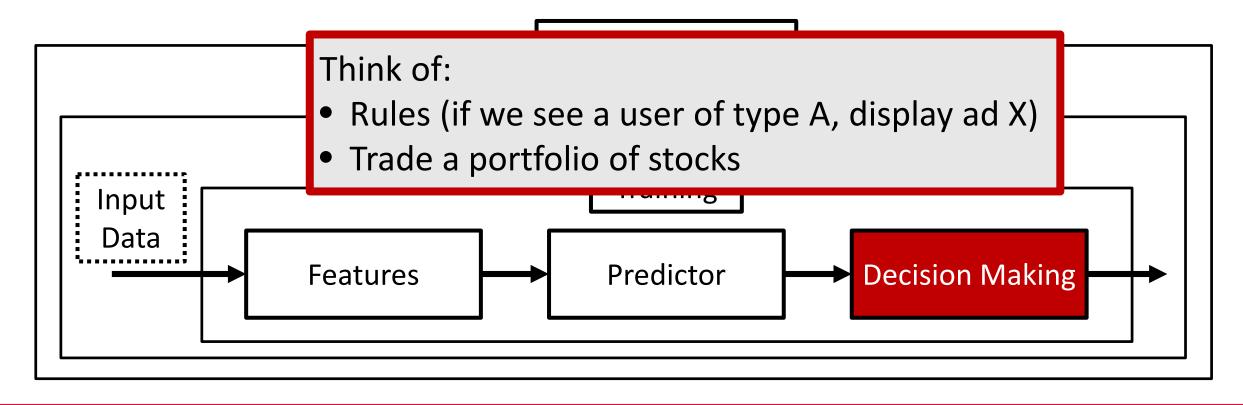




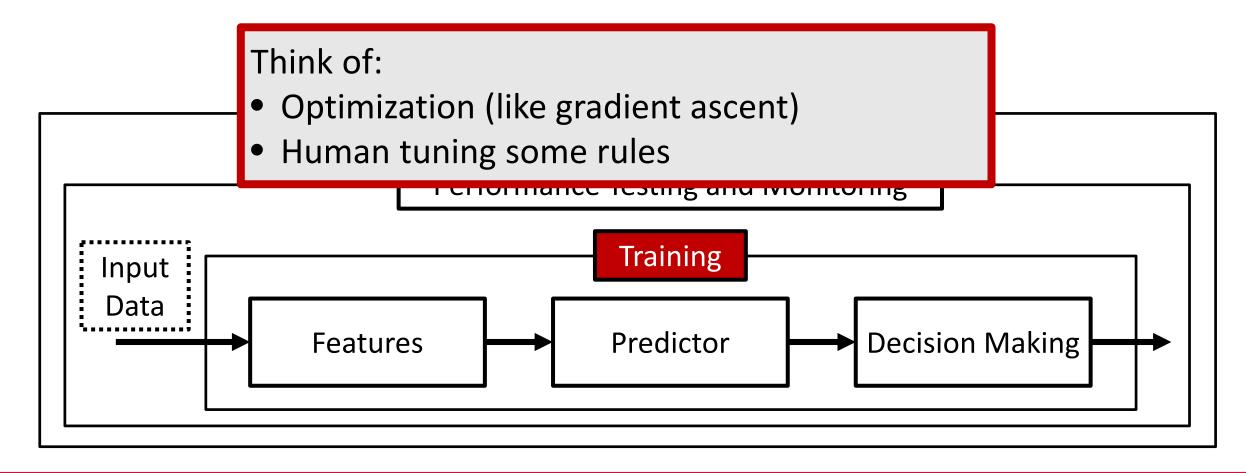








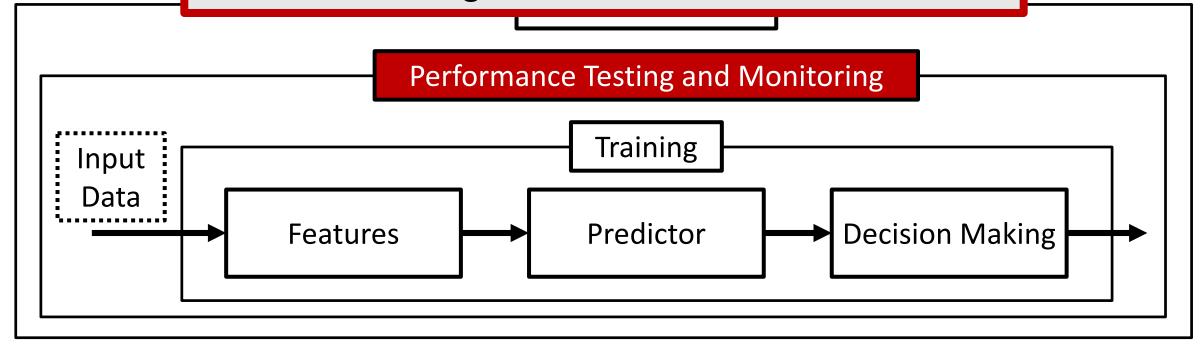






Think of:

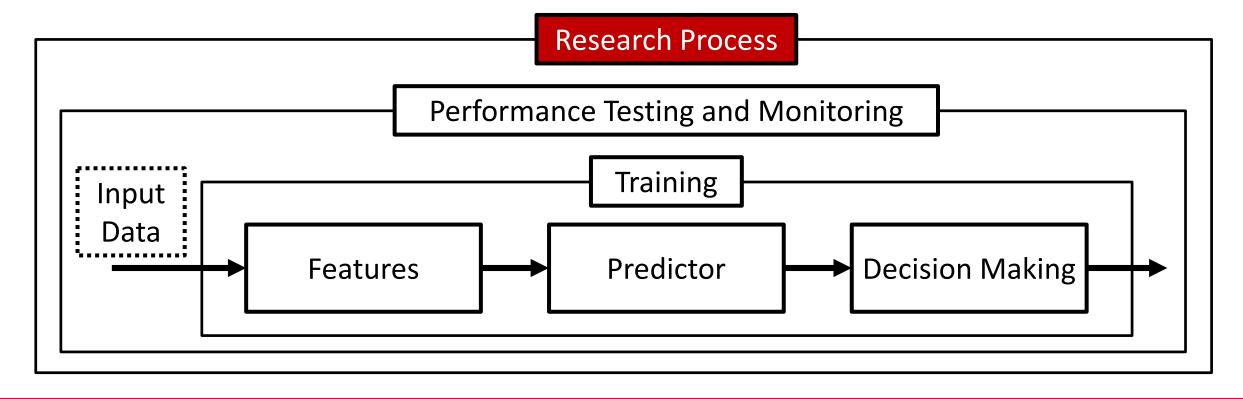
- Computing out-of-sample performance
- Comparing live performance to a historical estimate
- Statistical testing



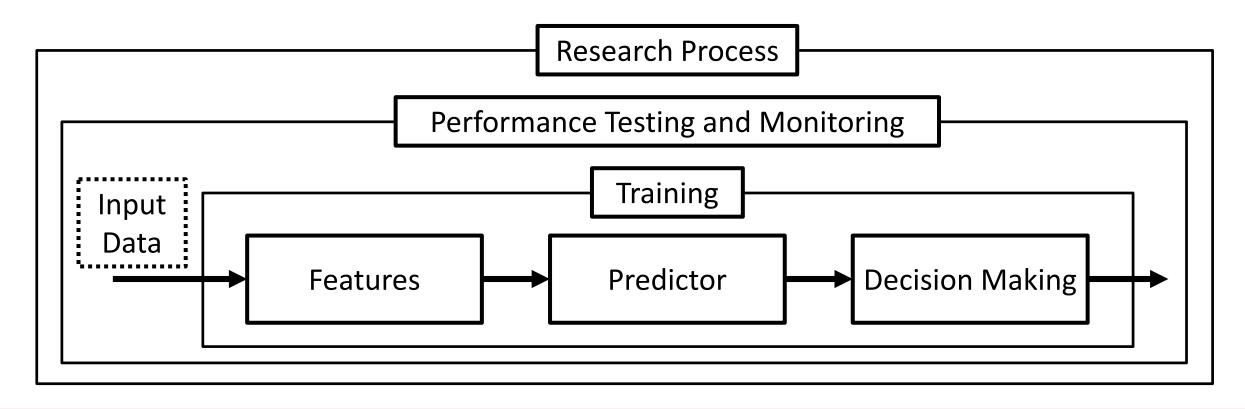


Think of:

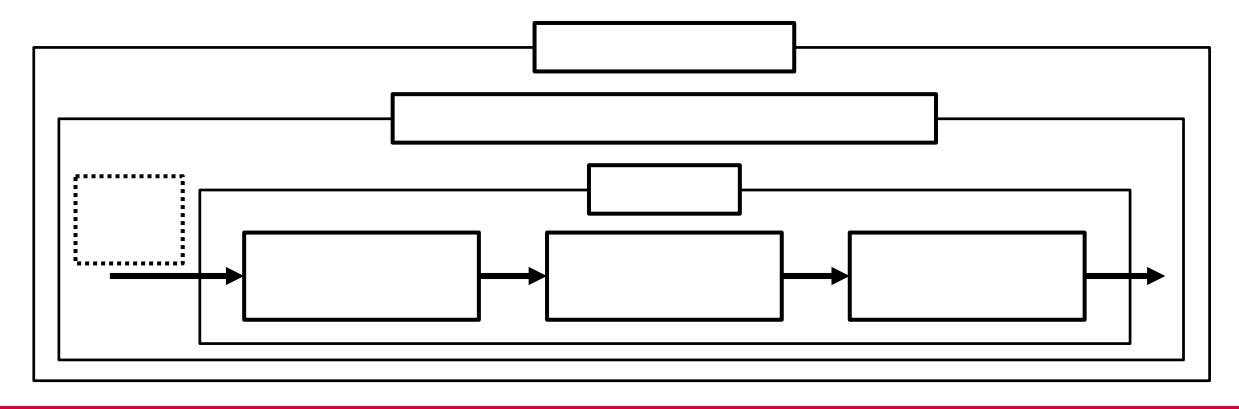
- How does the system get improved?
- What happens when something stop working well?













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



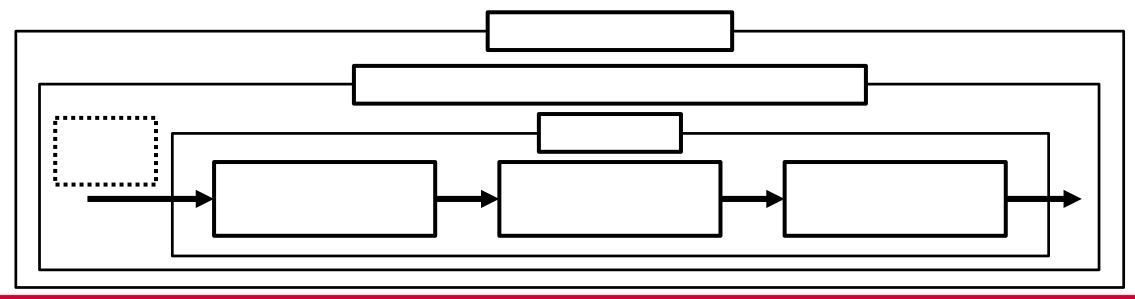
Find the Fuzzy-Power Words Game

- 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)





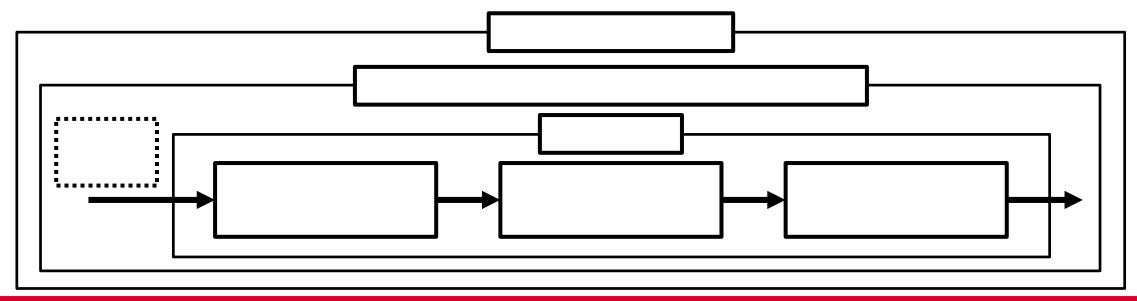








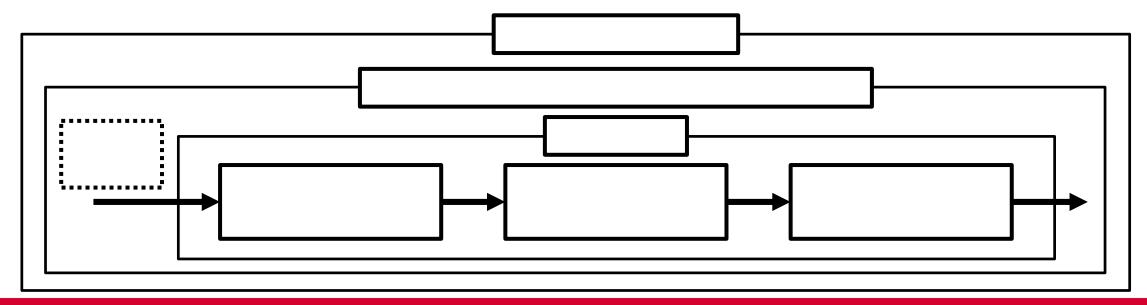
Al Trading through the Combination of the Wisdom of the Crowd and Expert Knowledge





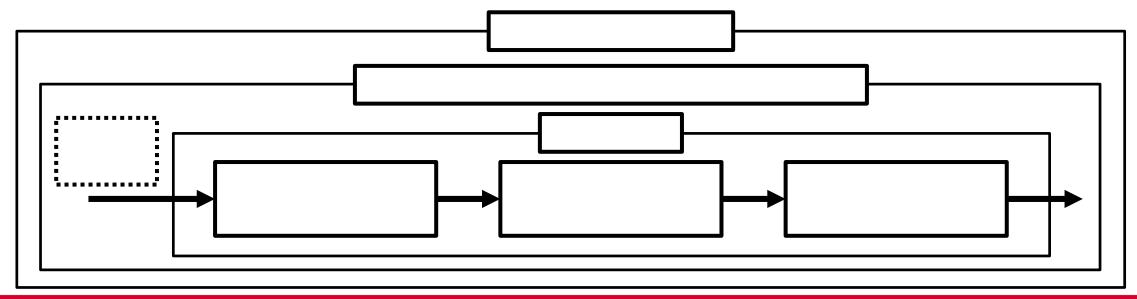


AI rading through the Combination of the Wisdom of the Crowd and Expert Knowledge





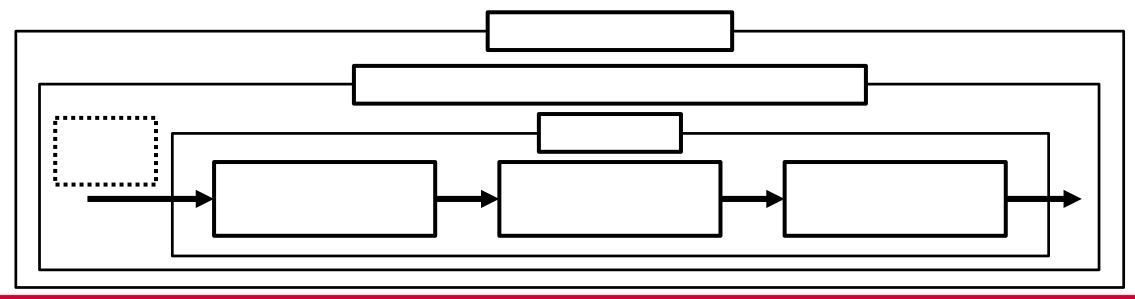
Al rading through the Combination of the Wisdom of the Crowd and Expert Knowledge







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





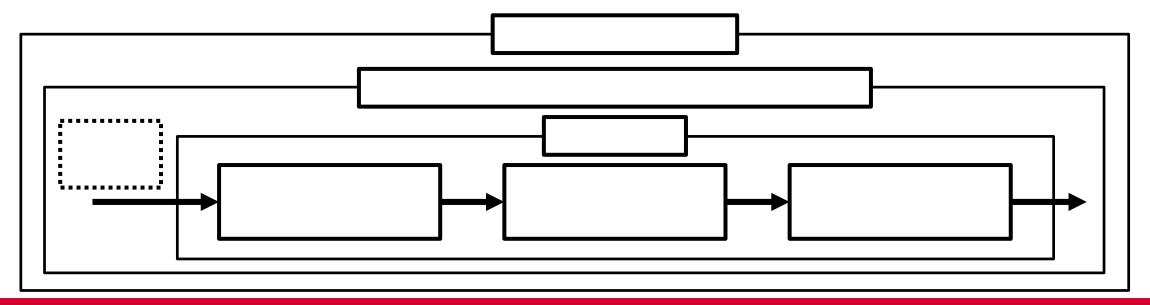


Al Trading through the Combination of the Wisdom of the Crowd and Expert Knowledge

Cutting edge analytics

Sentiment of social media

Expert insights





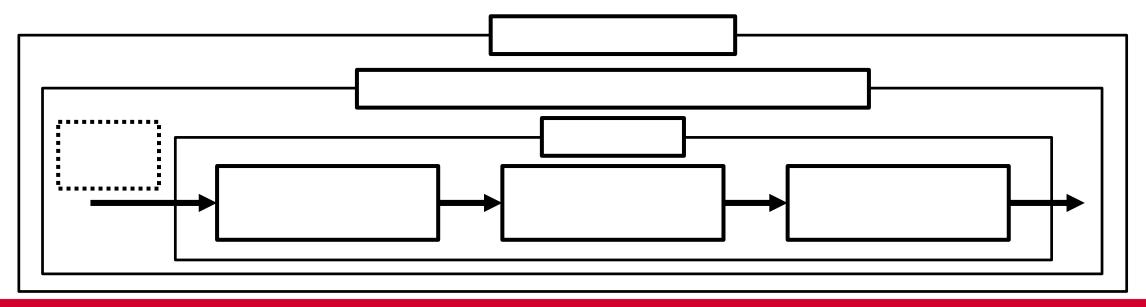


Al Trading through the Combination of the Wisdom of the Crowd and Expert Knowledge

Cutting edge analytics

Sentiment of social media

Expert insights







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

Cutting edge analytics

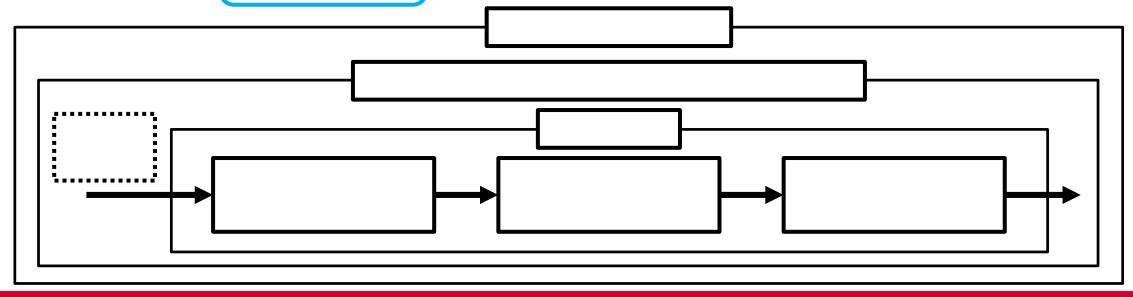
Sentiment of social media

Expett insights

Mathematical quantification of company health



Public expectations







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

Cutting edge analytics

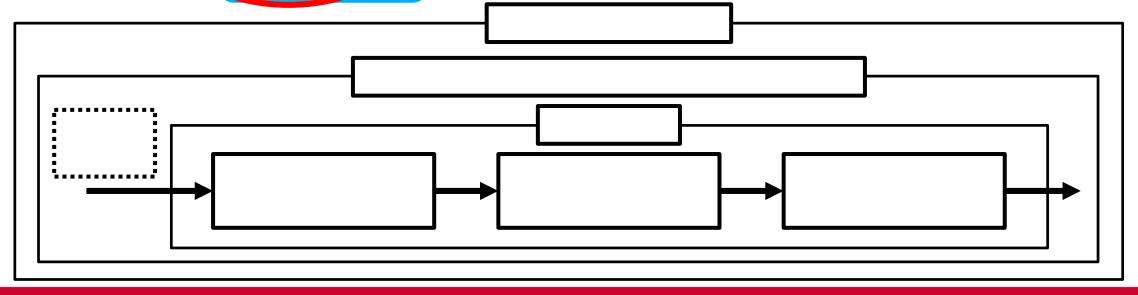
Sentiment of social media

Expett insights

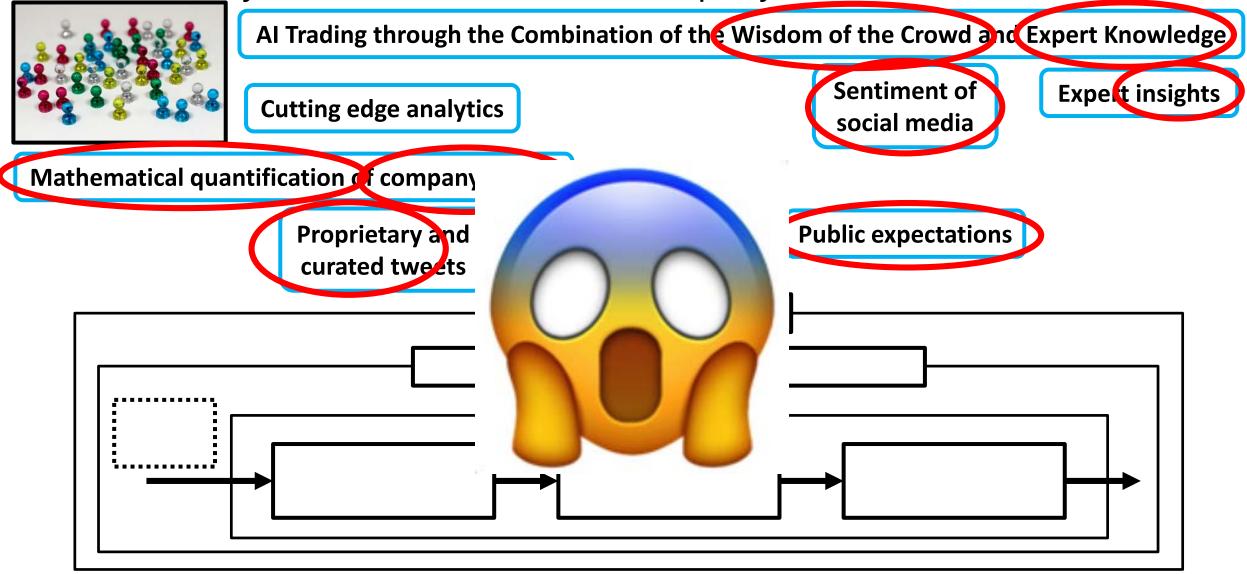
Mathematical quantification of company health

Proprietary and curated tweets

Public expectations











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

Cutting edge analytics

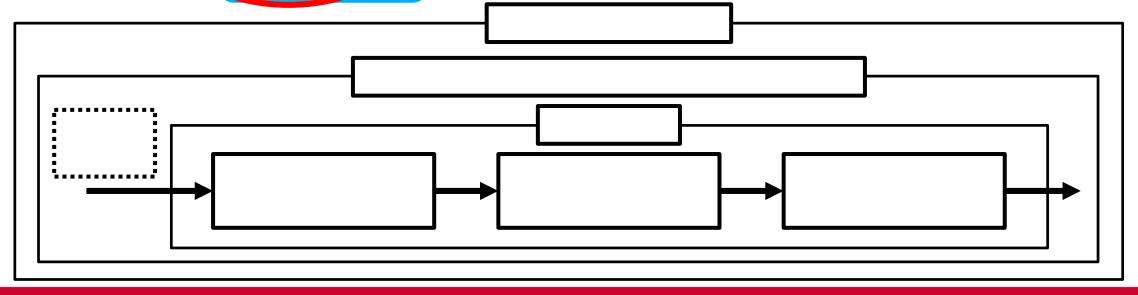
Sentiment of social media

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

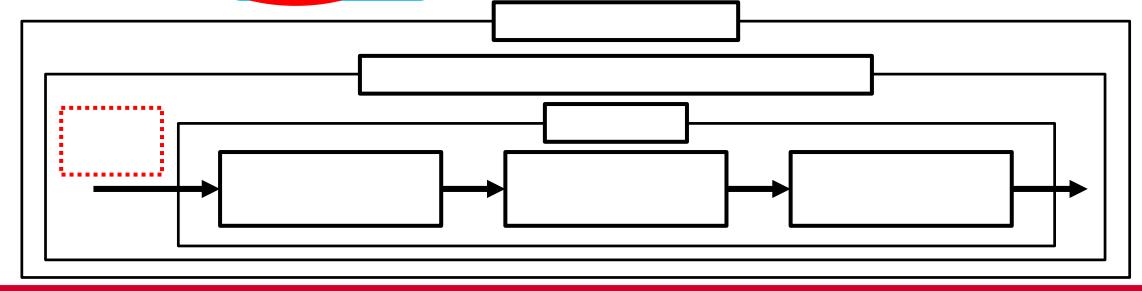
Sentiment of social media

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

Sentiment of social media

Expett insights

Mathematical quantification of company health

Proprietary and curated tweets

Public expectations

Tweets from humanselected accounts





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

Positive/negative

Proprietary and curated tweets

Public expectations







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

Cutting edge analytics

Sentiment of social media

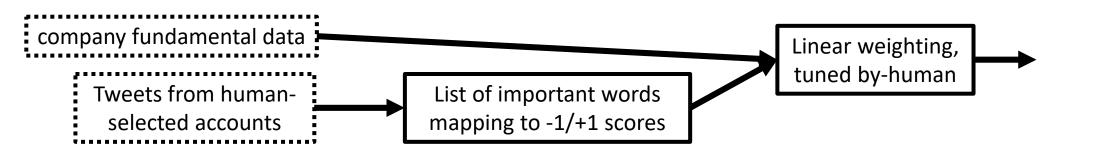
Expett insights

Mathematical quantification of company health

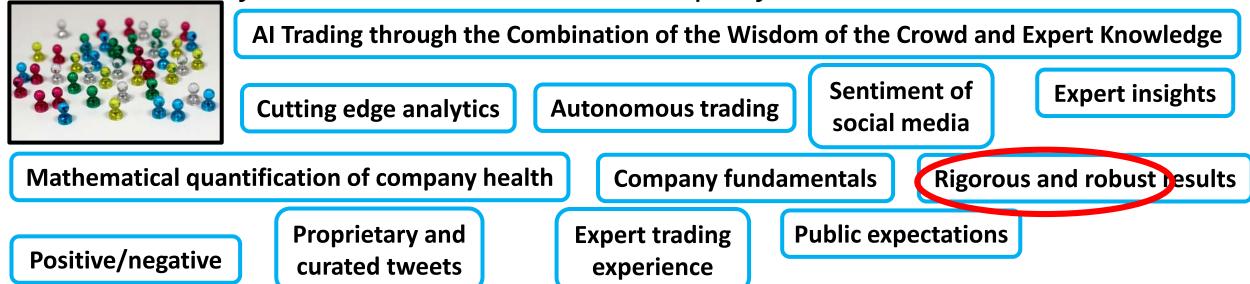
Positive/negative

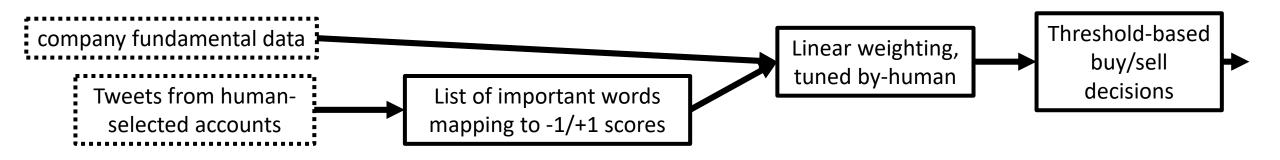
Proprietary and curated tweets

Public expectations











- They only show in-sample performance
 - (or don't clearly answer what is in-sample / out-of-sample)



- 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

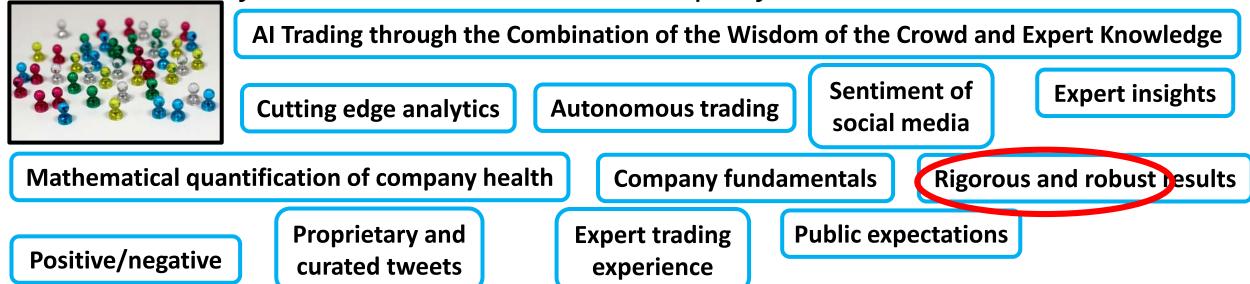


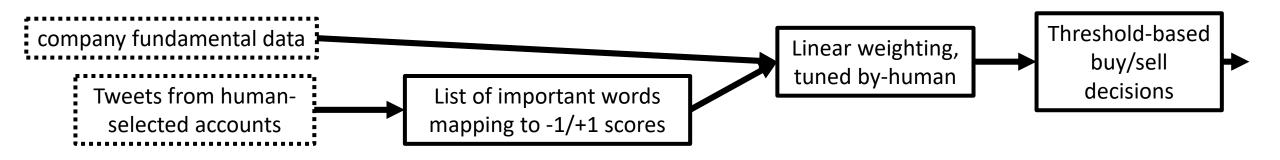
- They only show in-sample performance
 - (or don't clearly answer what is in-sample / out-of-sample)
- They don't have clear answers to expected future system performance with some understanding of the future performance's confidence
- They cite intuitive agreement as sufficient:
 - evidence of good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



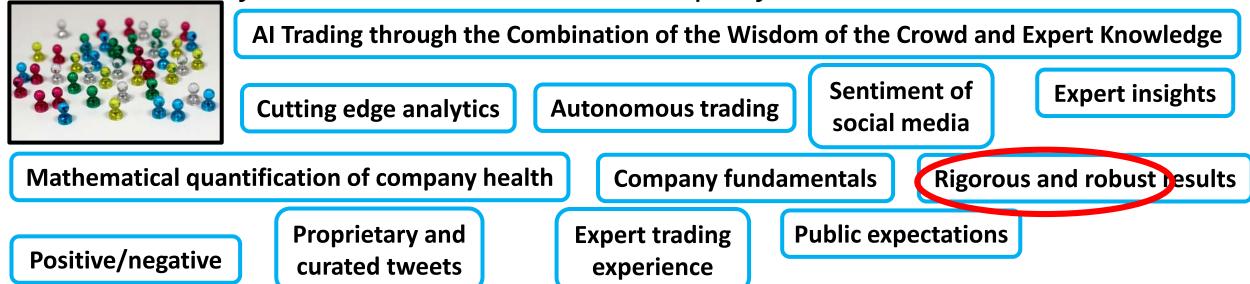
- They only show in-sample performance
 - (or don't clearly answer what is in-sample / out-of-sample)
- They don't have clear answers to expected future system performance with some understanding of the future performance's confidence
- They cite intuitive agreement as sufficient:
 - evidence of good future performance
 - justification for their methodology
- They are using a "novel" method without demonstrating how existing methods perform worse

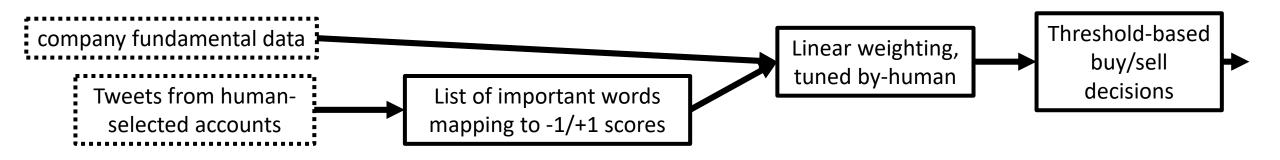




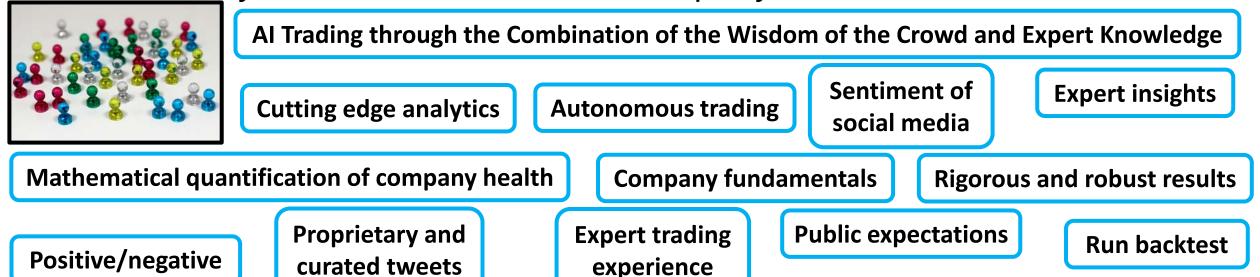


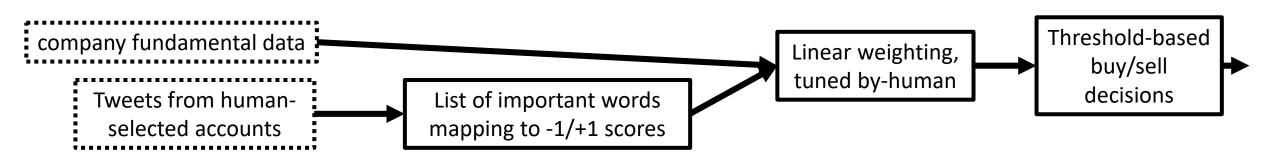




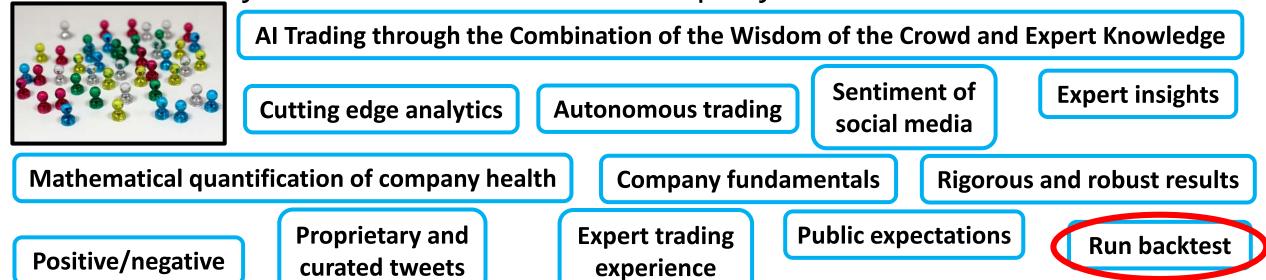


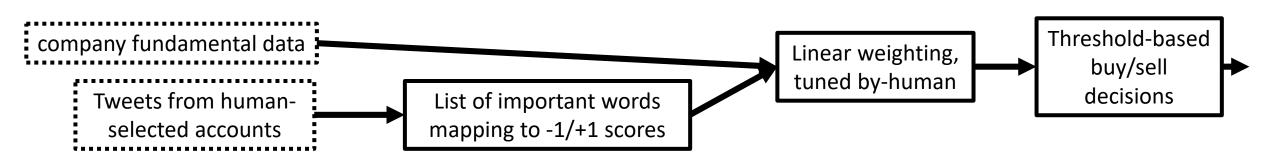








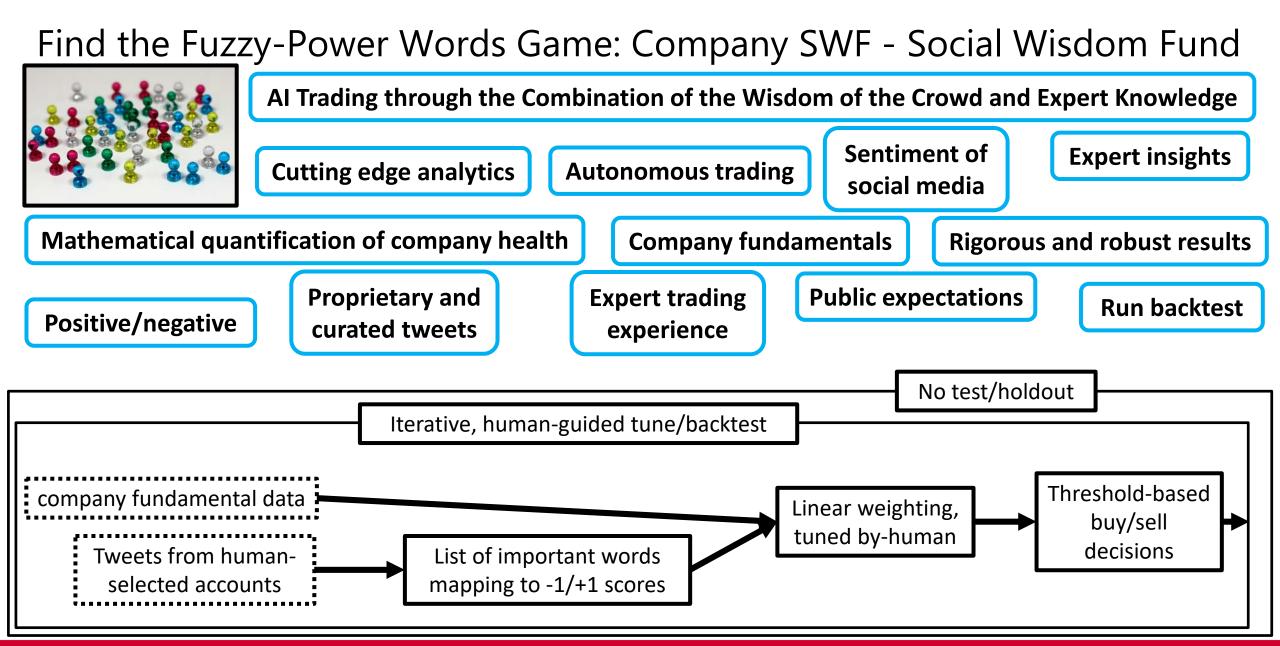


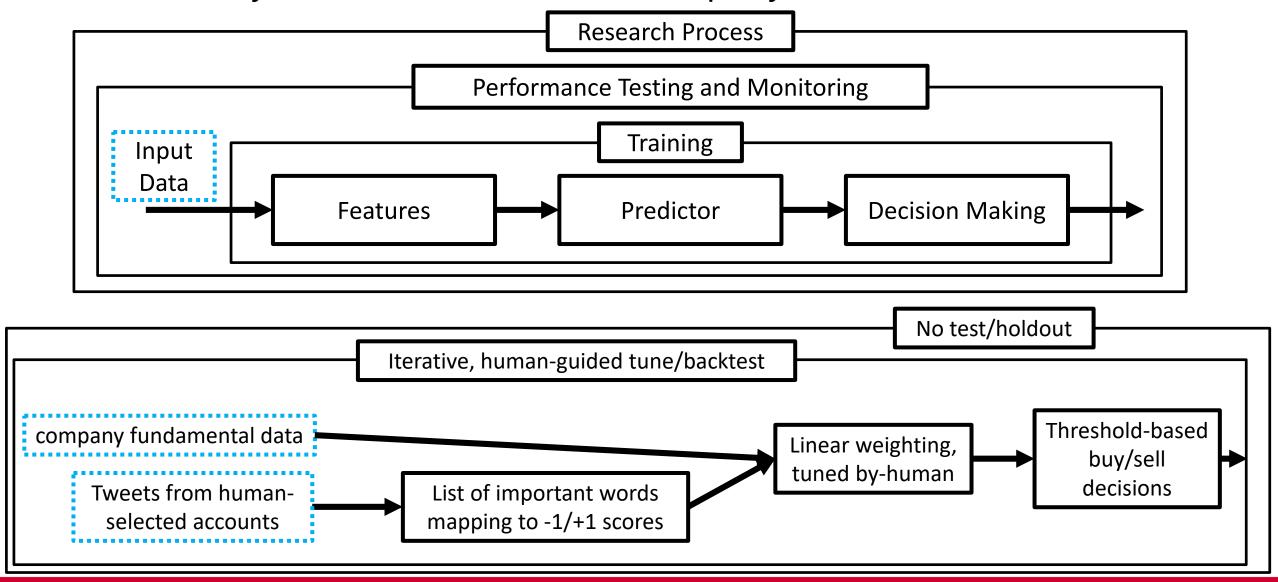


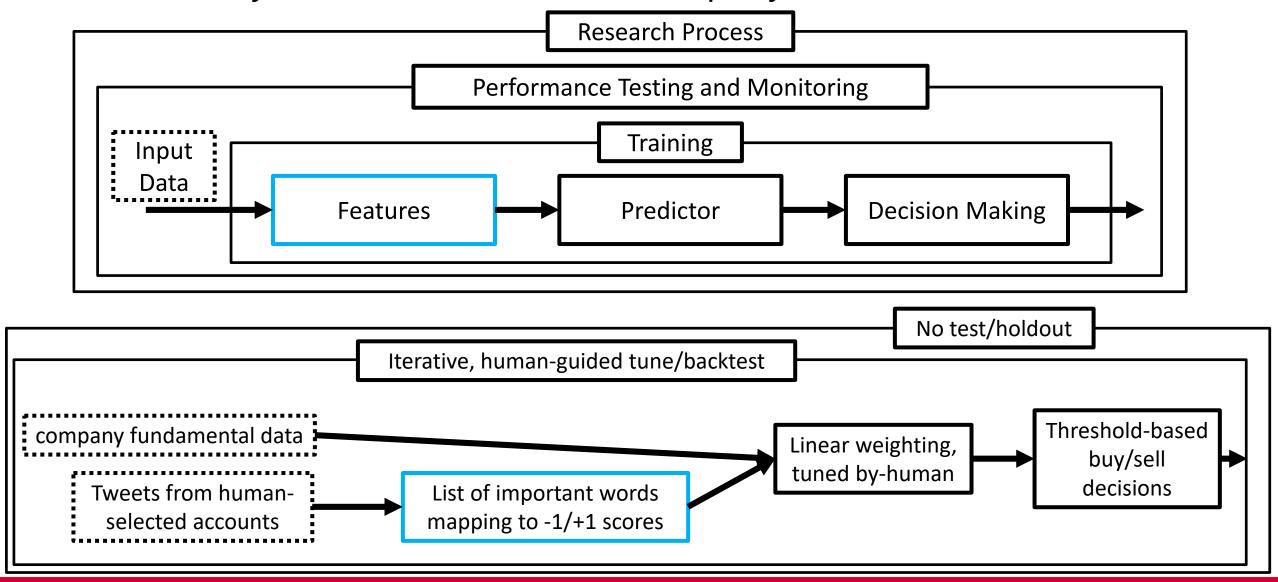


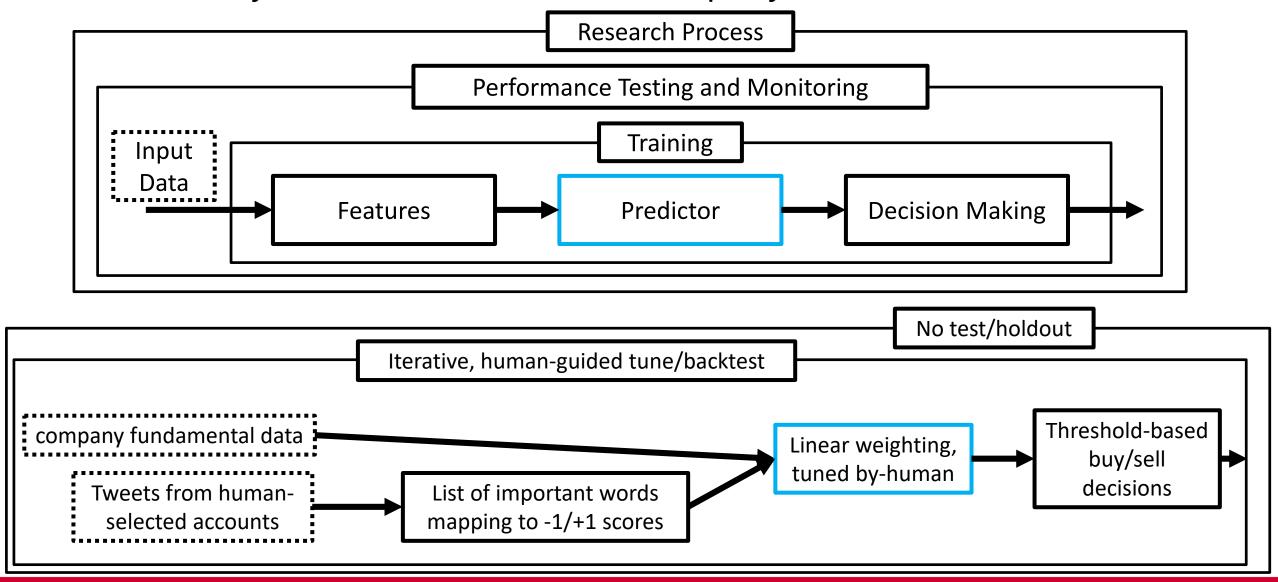
Find the Fuzzy-Power Words Game: Company SWF - Social Wisdom Fund Al Trading through the Combination of the Wisdom of the Crowd and Expert Knowledge Sentiment of **Expert insights Autonomous trading Cutting edge analytics** social media Mathematical quantification of company health **Company fundamentals 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

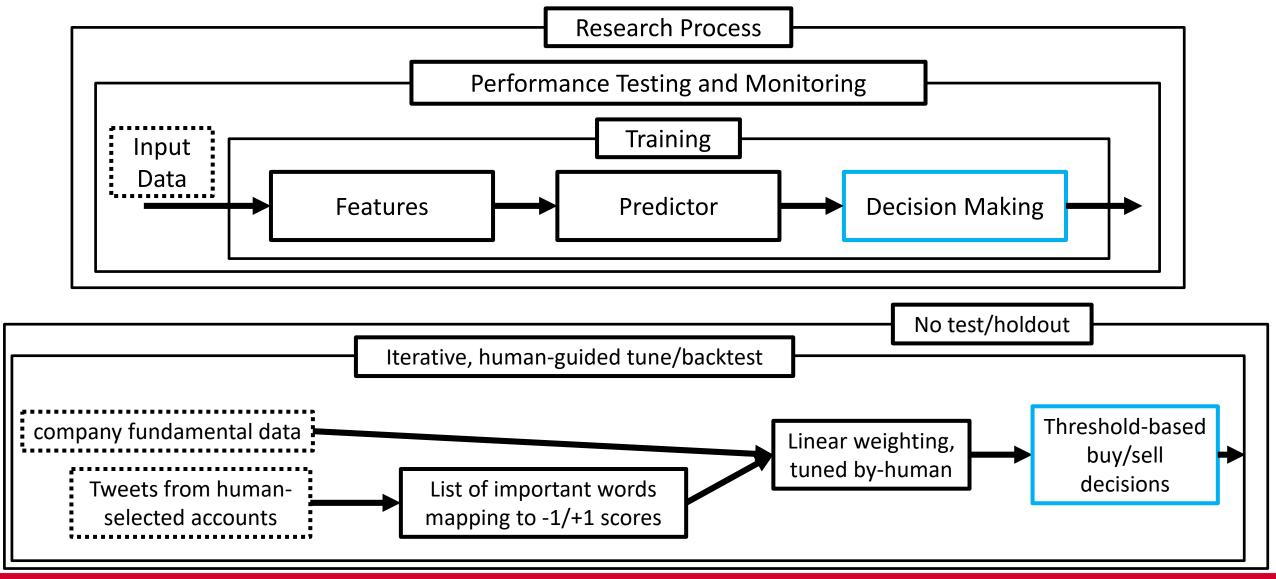


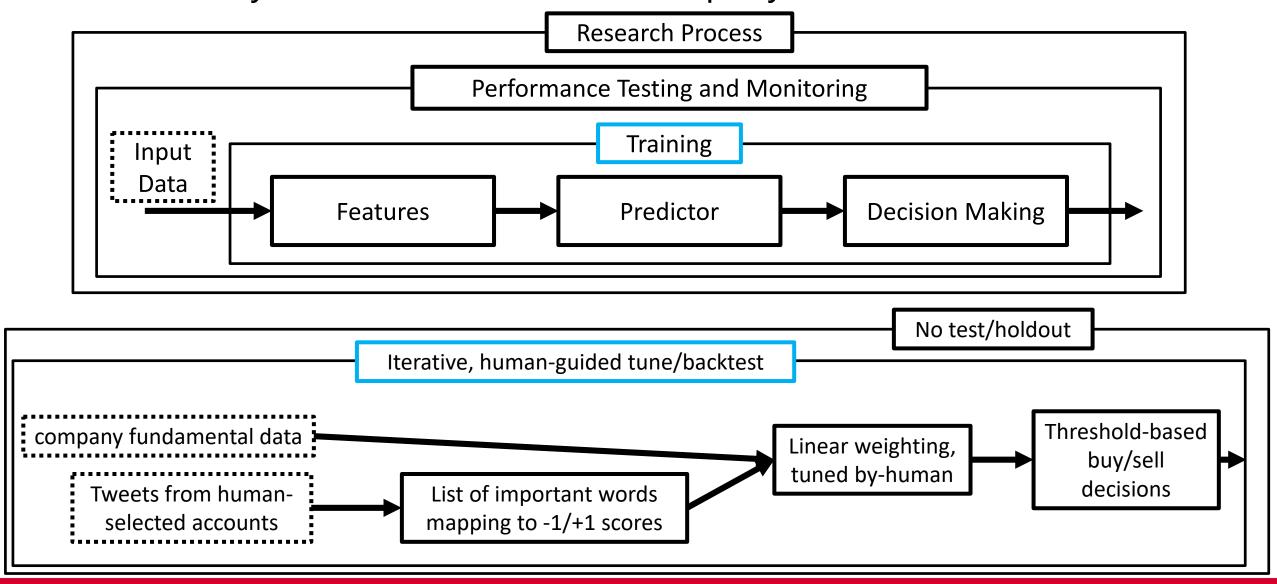


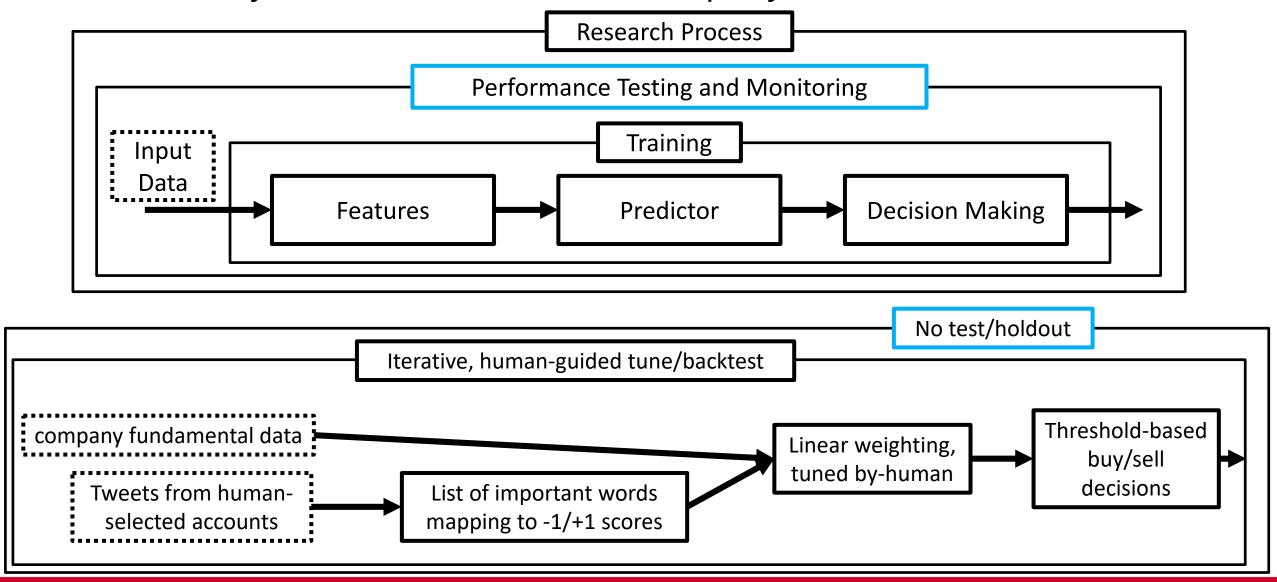


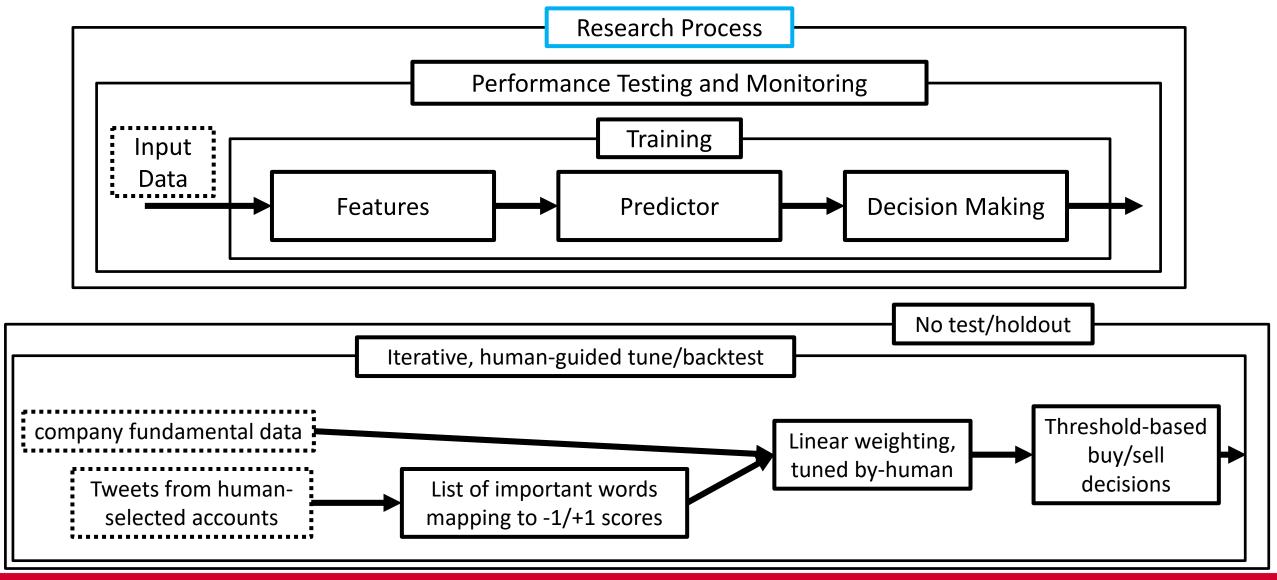










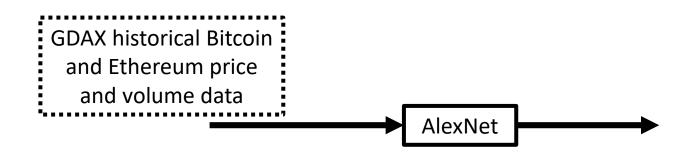


Find the Fuzzy-Power Words Game: Company SWF - Social Wisdom Fund AI Trading through the Combination of the Wisdom of the Crowd and Expert Knowledge Sentiment of **Expert insights Cutting edge analytics Autonomous trading** social media Mathematical quantification of company health **Company fundamentals Rigorous and robust results Proprietary and Expert trading Public expectations Run backtest** Positive/negative curated tweets experience No test/holdout Iterative, human-guided tune/backtest market data and company fundamental data Common Tweets from economic model of companies human-selected Average Threshold-based Mapping of List of accounts scores per buy/sell words to important Linear weighting, company decisions -1/+1 scores words tuned by-human by day

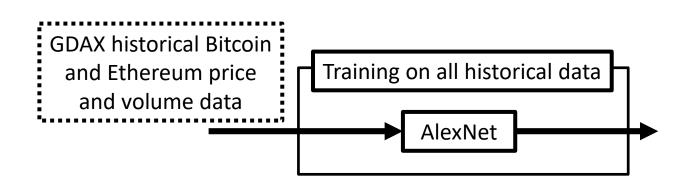


GDAX historical Bitcoin and Ethereum price and volume data

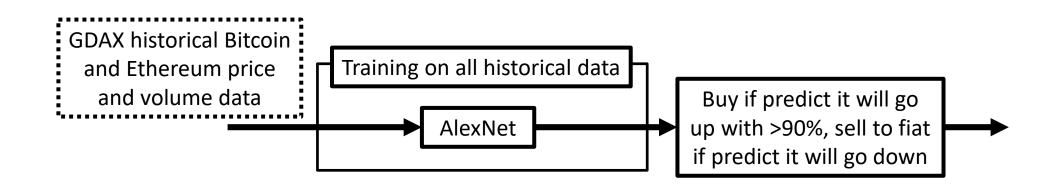




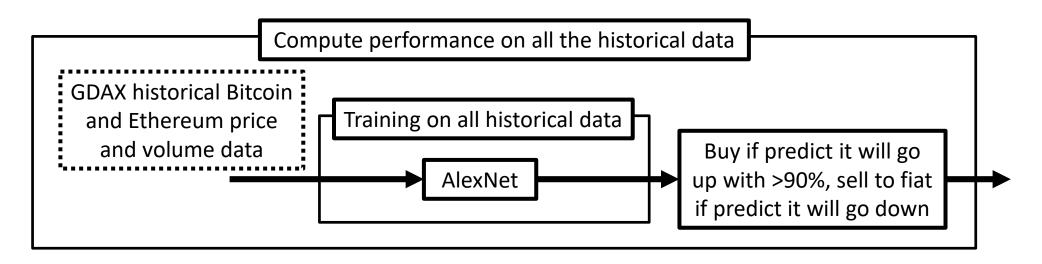




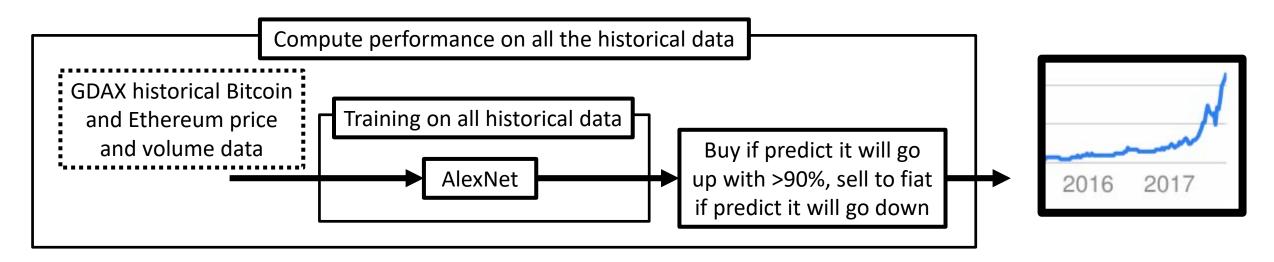




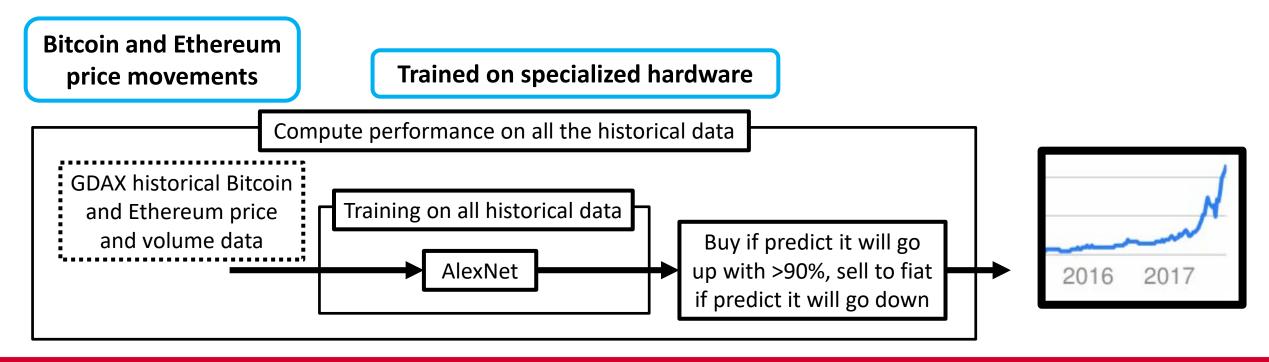




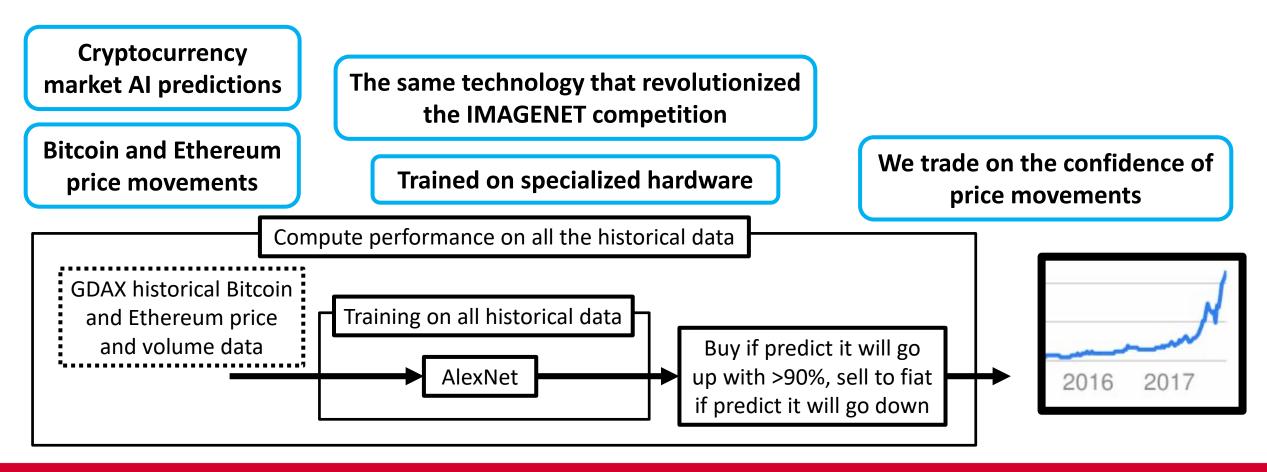


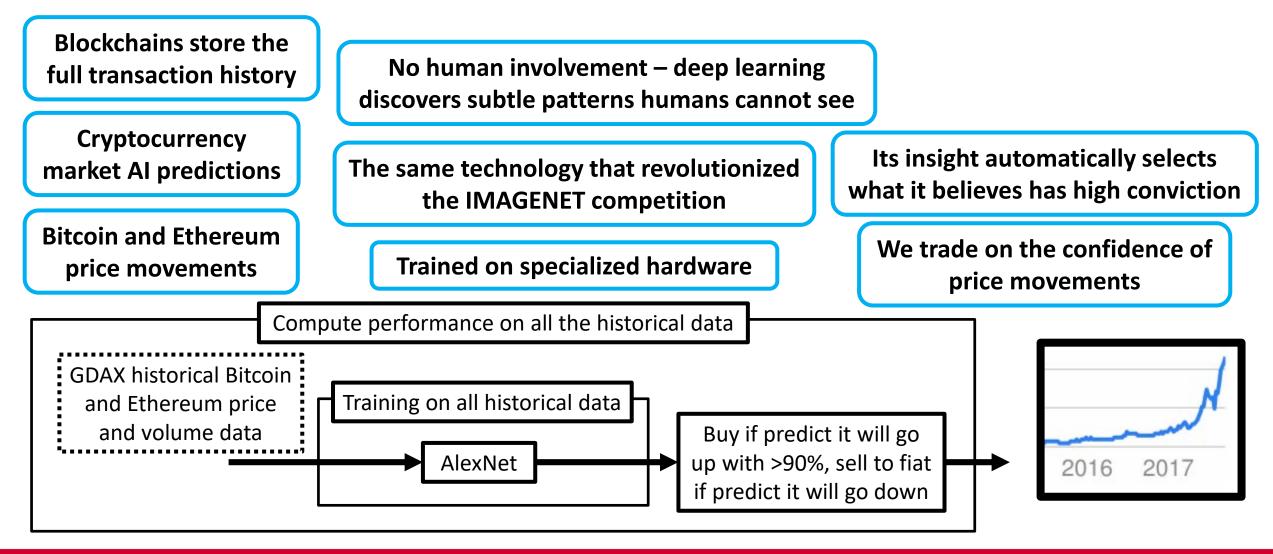














Deep Learning of the Blockchain Blockchains store the No human involvement – deep learning full transaction history discovers subtle patterns humans cannot see **Cryptocurrency** Its insight automatically selects The same technology that revolutionized market AI predictions what it believes has high 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



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



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



Blockchains store the full transaction history

Cryptocurrency market AI predictions

Bitcoin and Ethereum price movements



Deep Learning of the Blockchain

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

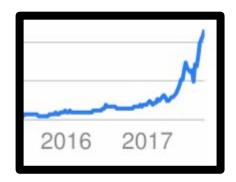


The same technology that revolutionized the IMAGENET competition

Trained on specialized hardware

Its insight automatically selects what it believes has high conviction

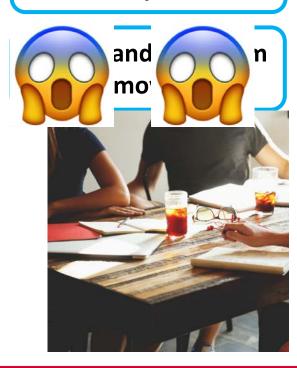
We trade on the confidence of price movements





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

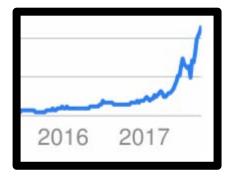


The same technology that revolutionized the IMAGENET competition

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.



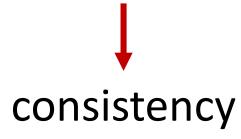
Components of a Productive ML Sniff Test

- 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?

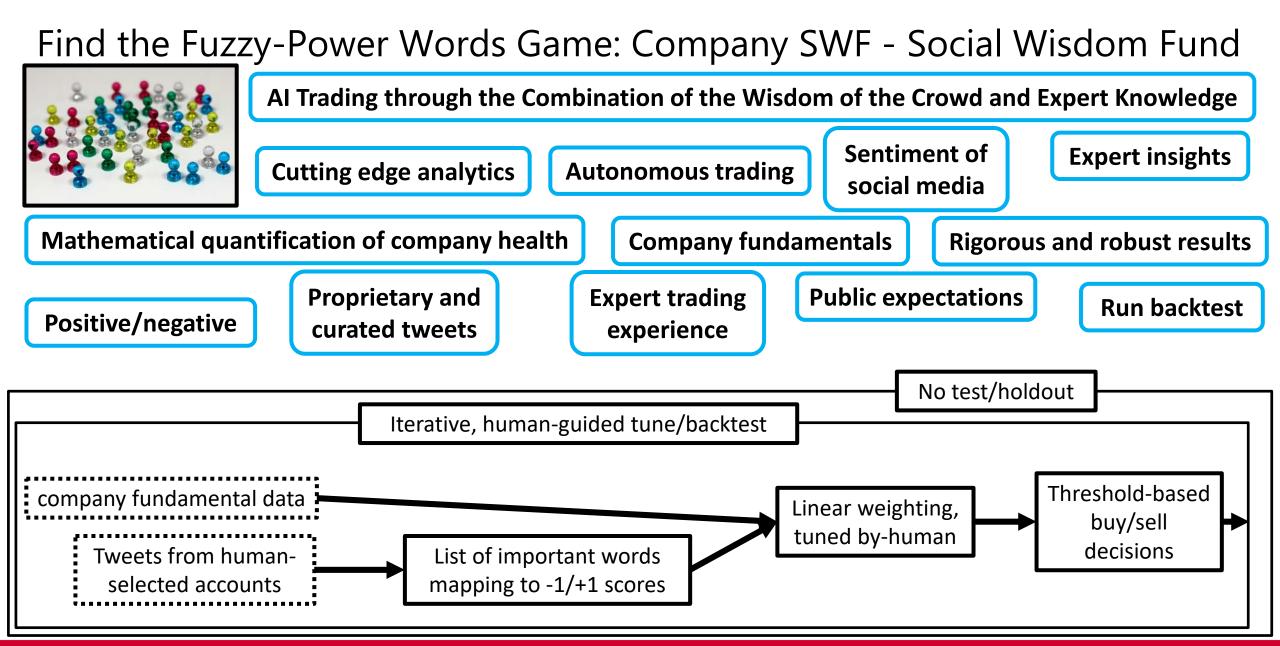


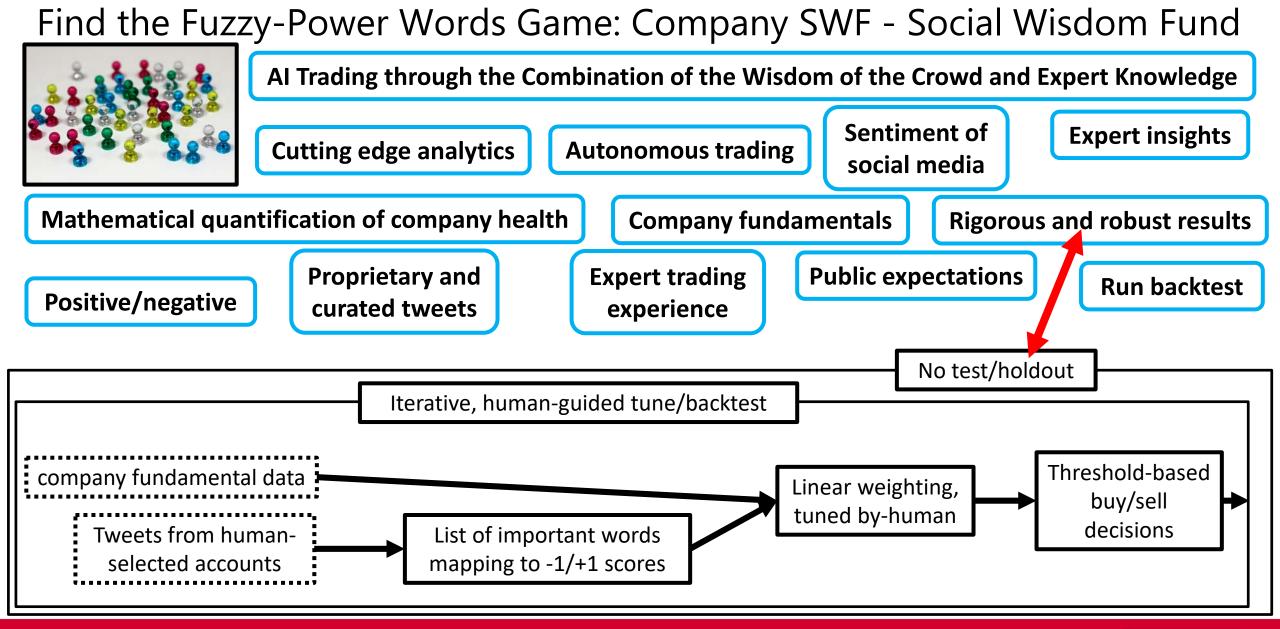


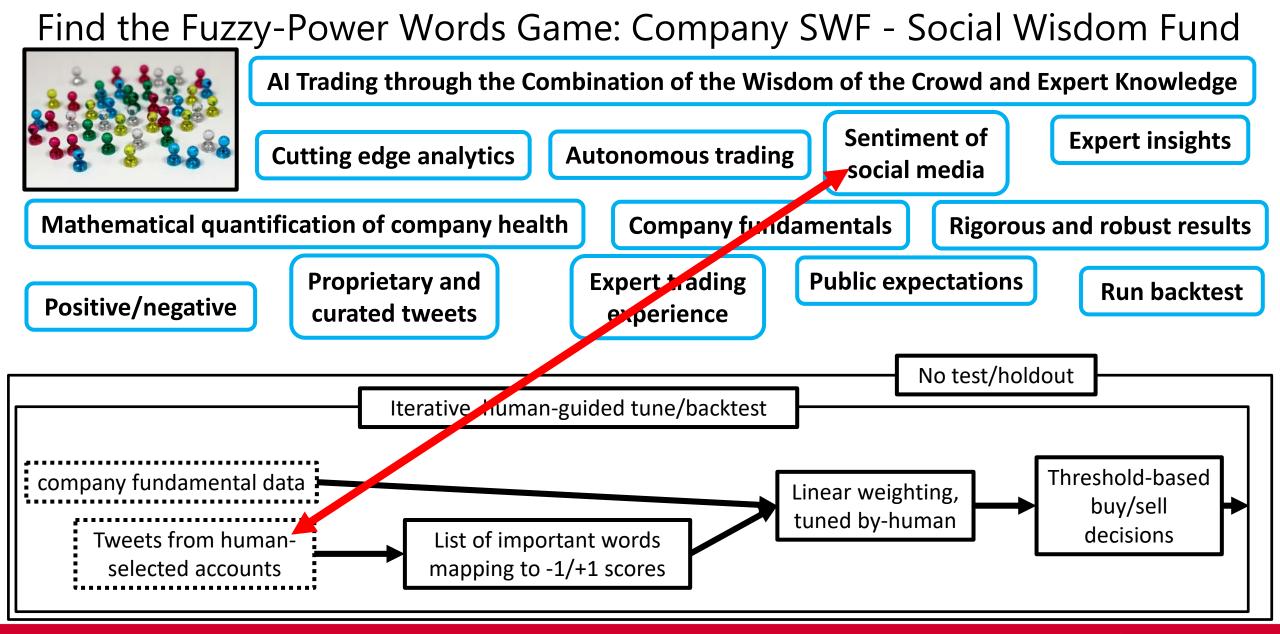
Integrity Gaps Across Hops

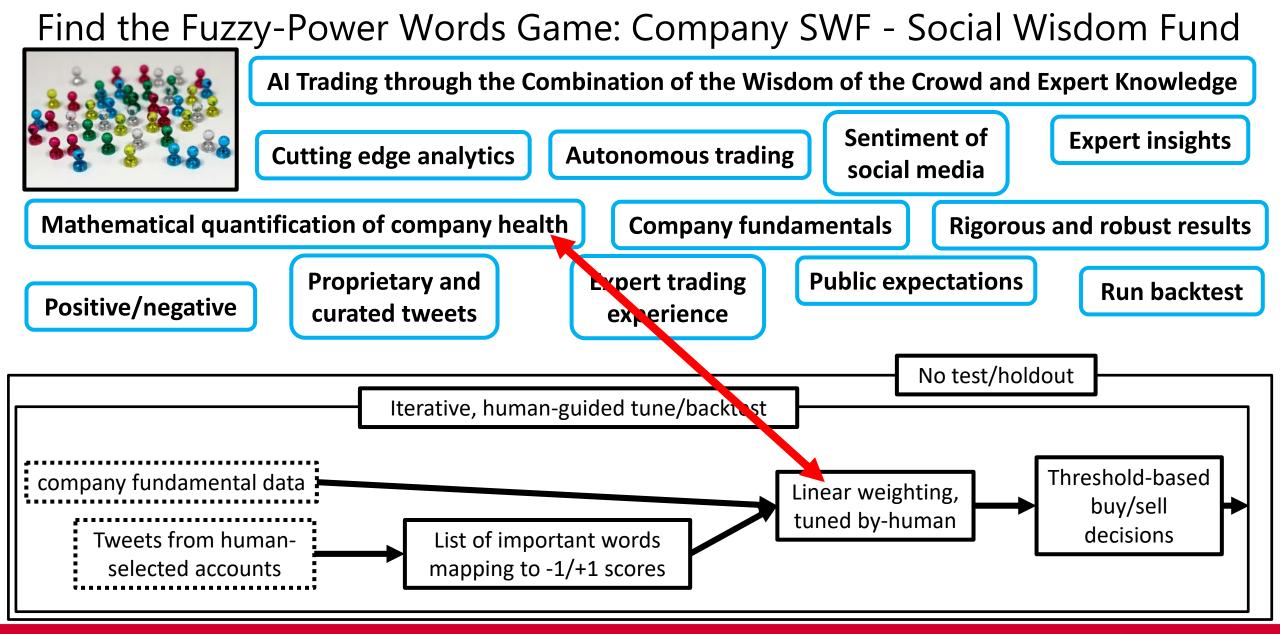
- Now look back at the diagram, how much integrity is there in each hop?
- The purpose here is to discover if these "integrity gaps" are that:
 - They simplified it for our benefit
 - They don't view the gap as a gap and it's our misunderstanding
 - They are trying to deceive us









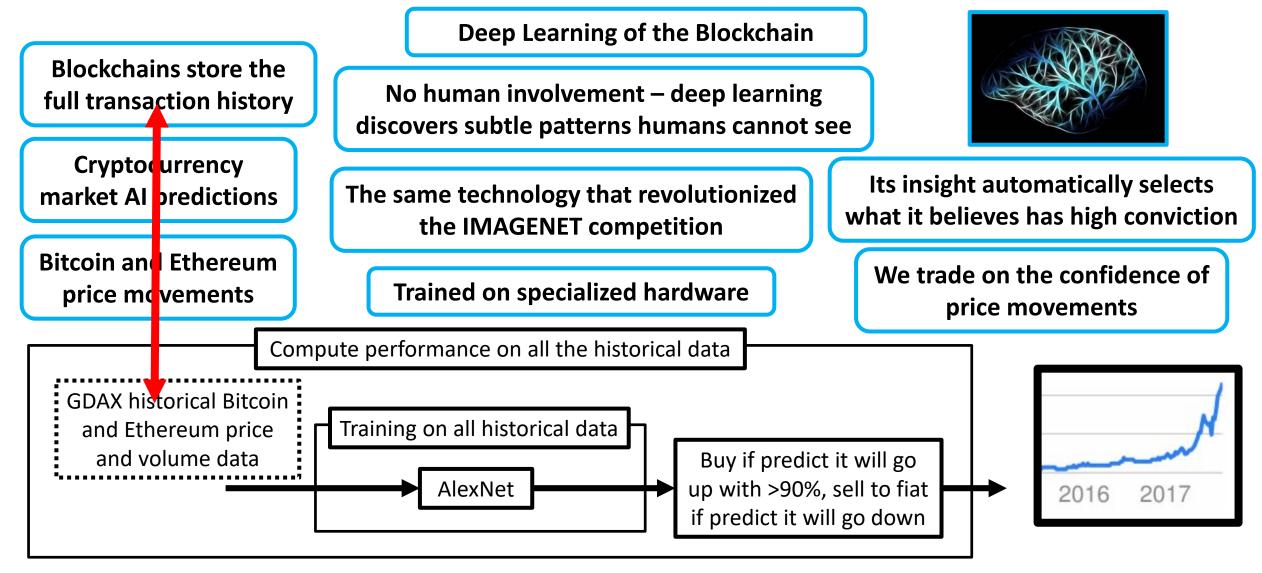


Find the Fuzzy-Power Words Game: Company DCC – Deep Crypto Capital

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

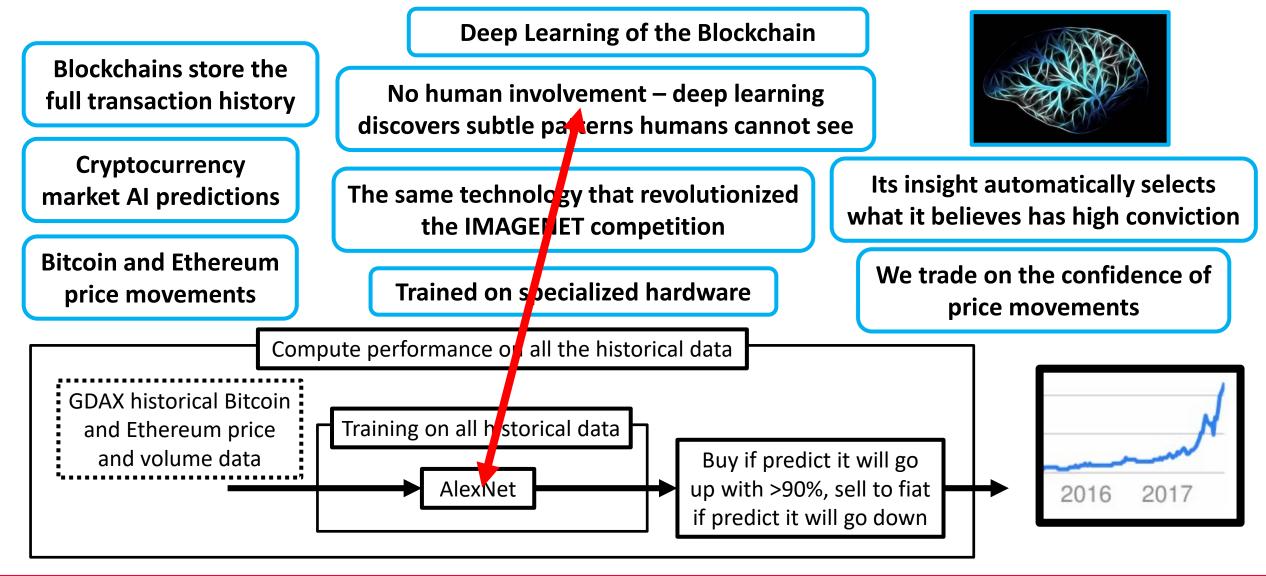


Find the Fuzzy-Power Words Game: Company DCC – Deep Crypto Capital





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



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

Decision making:

Monitoring for performance changes: * What is the meaning of the decisions you are making? * Where does the data come from? * How are you monitoring for performance changes? * On what timescales is your system outputting decisions? * How much history do you have? * How often do you expect to detect changes in performance? * What is the resolution of your data? * What type of representation do you use to go from a prediction to a decision? * Do you have methods for early-detection of performance changes for each individual * Are there any large gaps or outages in your data? * What alternate methods did you try? Why were those passed on? component before it shows up in overall performance? * What kind of sanity checking, cleaning, and outlier detection/removal do you do? * How much human domain knowledge is imbedded in your decision making representation? * When has your monitoring caught a change in performance? * How do you check for changes in the data format? How many times has that happened? * How does your system quantify its uncertainty in a prediction? * How do you think about the difference between an anomalous environmental condition and a * What is the biggest source of noise in the data? * Why does your decision making representation make sense for the decisions you want to make? change in performance? * Who else has access to the same data? * Has anyone used data like yours to solve a problem like yours? Training: * How much "human curation" is in your data? Research process: * What parts of your system "learn" from data? * What filtering is in place? * Describe your overall research philosophy * How is the data stored? * Where do your labels come from? How accurate are they? * For any change that is made to the overall system (method, implementation, etc), what is * Are there sporadic performance-effecting latencies in your data arrival? * How much human domain knowledge is in the fitting process? the process that validate and approves the change? * Can you give me specific examples of what your data actually is? * What is the rough ratio of (# data points)/(# features)? * How often is the methodology or a component of the system changed? * 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 * 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 * Roughly what order of magnitude of parameters are you fitting? performance? Why did that happen? How was your process changed to prevent this from happening * How do you represent features in your system? * What are alterative objective functions you have tried? again in the future? * 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? * What is the likely next research piece to make it into production? * What alternative optimization techniques have you previously tried? Why were those * What roles comprise your research team? Why? * How much human domain knowledge is imbedded in your features? * Do you normalize/transform your features somehow? * How do you allocate time across your team? * How do you handle heterogenous data sources? * How do you understand if your system is overfitting/underfitting? * What part of your system keeps you up at night? Why? * Roughly, how many features do you use? * How often do you re-fit your representations? How much does that increase your performance? * What has worked much better/worse than you had expected? * (If feature selection, dimensionality reduction, etc. methods are used) * How is your live system influencing/corrupting your future data? How are you correcting for * Why were these methods chosen? Performance testing: * What effect do they have on the system's overall performance? * How do you test the performance of your overall system? * What other data sources have you investigated? * Why do these features make sense for the decisions you want to make? * How closely does your in-sample data represent your out-of-sample? * How do you test the performance of single components of your system (e.g., the decision * What is the meaning of the prediction output? * Exactly how large is your train/test/holdout sets? How are they kept separate? * What type of representation do you use to go from features to a prediction? * What assumptions is your overall approach making? How have you validated these assumptions * On what timescales is your system outputting predictions? * How does your system quantify its uncertainty in a prediction? * What are the metrics you use to measure performance across your system? * Why did you chose that representation from the many, many of other methods? * What is your overall performance? With confidences. * What alternate methods did you try? Why were those passed on? * How do common baseline methods perform on your problem? With performance and confidences. * How much human domain knowledge is imbedded in your prediction representation? * 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 are other successful applications of your chosen representation?

* What do you believe is the maximum achievable performance? Why?

* Does your performance make intuitive sense to you? Why or why not?

* How have the dynamics of your data/problem changed over time?

differences? How do you represent and compensate for them?

simulated data generated?

(Don't worry, you don't have to read it all. It's there so you have lists of questions for later.) alphafeatures.com/oreilly ai conference questions.txt

* How much do your estimated and live performances differ? What are the sources of these

* Do you validate against simulated data where you know your assumptions hold? How is the



* Why does your predictor representation make sense for the decisions you want to make?

* How do you validate that you increase performance by adding additional models?

* Do you find most of your performance comes from a few of the models?

* If more than one predictor (for example, using ensembles):

* Roughly how many models do you use?

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



- Tricks to pull out in the meeting
 - Purposefully ask a wrong question 1 out of 5 times (super-power)



- 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



- 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



- 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
 - Charitable but ruthless drive for clarity and keeping vocabulary synced (say this!)

- 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
 - Charitable but ruthless drive for clarity and keeping vocabulary synced (say this!)
 - (If you're a tech person) Think of yourself as a compiler for their methods



- 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
 - Charitable but ruthless drive for clarity and keeping vocabulary synced (say this!)
 - (If you're a tech person) Think of yourself as a compiler for their methods
 - You are on the easy side of the table (burden of proof is on the seller)



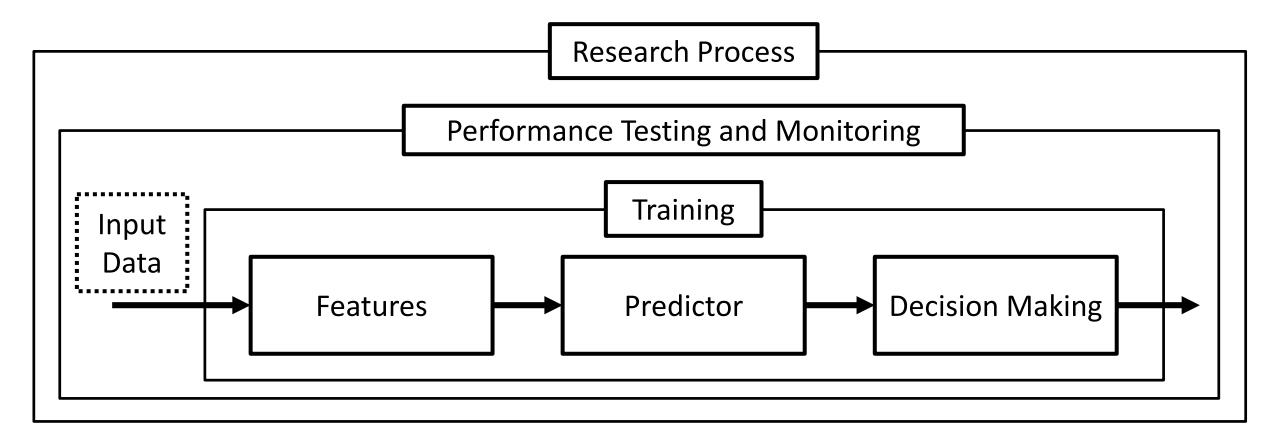
- Tricks to pull out in the meeting
 - Purposefully ask a wrong question 1 out of 5 times (super-power)
 - Jump on strangely out of place, overly precise jargon
- Helpful mindsets
 - Charitable but ruthless drive for clarity and keeping vocabulary synced (say this!)
 - (If you're a tech person) Think of yourself as a compiler for their methods
 - 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



- 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
 - Charitable but ruthless drive for clarity and keeping vocabulary synced (say this!)
 - (If you're a tech person) Think of yourself as a compiler for their methods
 - 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

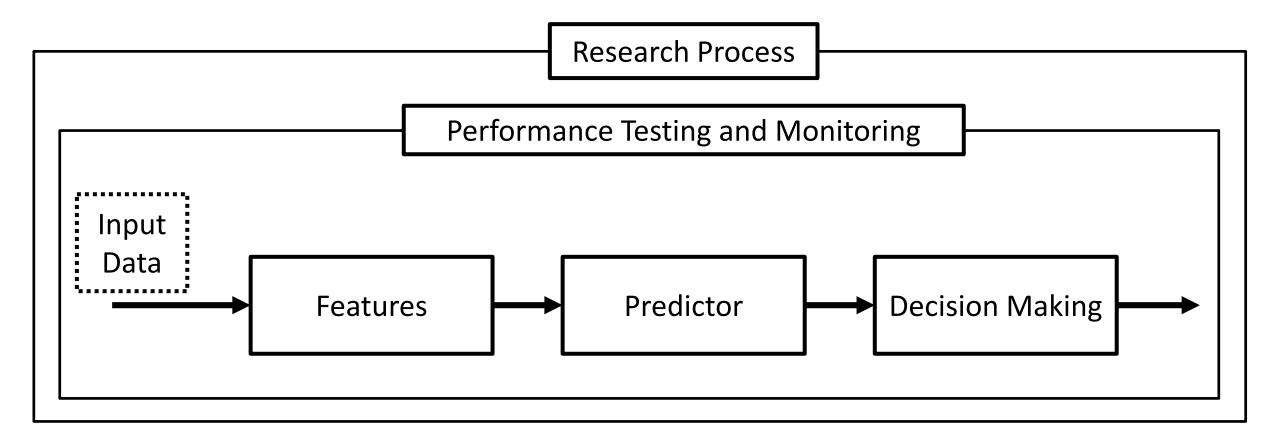


What about an Al system?





What about an AI system?





A Practical Guide to Conducting an Al Snake Oil Sniff Test



A Practical Guide to Conducting an Al Snake Oil Sniff Test

Understanding what they're doing



A Practical Guide to Conducting an AI Snake Oil Sniff Test

Understanding what they're doing

Understanding of ML core concepts



A Practical Guide to Conducting an AI Snake Oil Sniff Test

Understanding what they're doing

Understanding of ML core concepts

Sniff test procedure



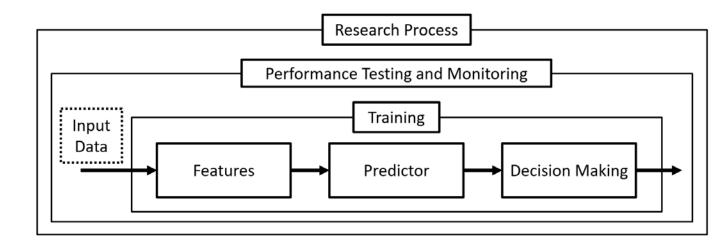
A Practical Guide to Conducting an AI Snake Oil Sniff Test

Understanding what they're doing

Understanding of ML core concepts

Sniff test procedure

Initial ML system mental picture





A Practical Guide to Conducting an AI Snake Oil Sniff Test

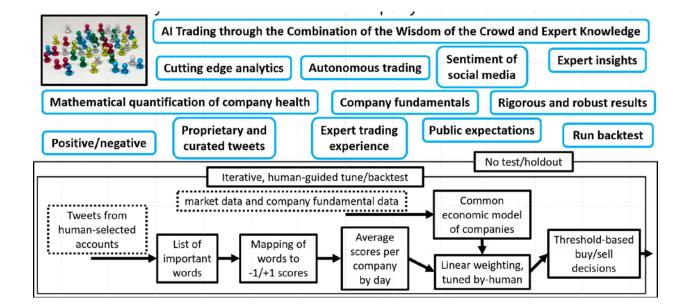
Understanding what they're doing

Understanding of ML core concepts

Sniff test procedure

Initial ML system mental picture

Find the fuzzy-power words



A Practical Guide to Conducting an AI Snake Oil Sniff Test

Understanding what they're doing

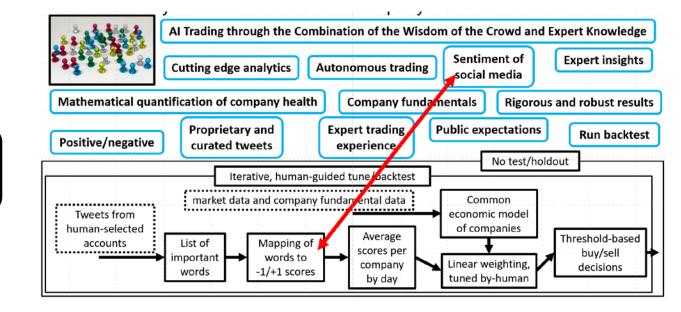
Understanding of ML core concepts

Sniff test procedure

Initial ML system mental picture

Find the fuzzy-power words

Integrity gaps





A Practical Guide to Conducting an AI Snake Oil Sniff Test

Understanding what they're doing

Understanding of ML core concepts

Sniff test procedure

Initial ML system mental picture

Find the fuzzy-power words

Integrity gaps

Lists of questions

Input data:

- * 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?
- * Do you believe there is systematic noise in your data somehow? How do you correct for it?

Features:

- * 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 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?

Predictor:

- * 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?
- * Do you explicitly regularize or measure/control the complexity your representation somehow?
- * 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?



A Practical Guide to Conducting an AI Snake Oil Sniff Test

Understanding what they're doing

Understanding of ML core concepts

Sniff test procedure

General tips

Initial ML system mental picture

Find the fuzzy-power words

Integrity gaps



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

Initial ML system mental picture

Find the fuzzy-power words

Integrity gaps

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

Initial ML system mental picture

Find the fuzzy-power words

Integrity gaps



A Practical Guide to Conducting an Al 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

Initial ML system mental picture

Find the fuzzy-power words

Benchmarks that industries care about

Integrity gaps

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

Initial ML system mental picture

Find the fuzzy-power words

Integrity Lists of questions

Benchmarks that industries care about

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

Initial ML system mental picture

Find the fuzzy-power words

Integrity gaps

Lists of questions

Benchmarks that industries care about

Detailed success/failure case studies



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

Initial ML system mental picture

Find the fuzzy-power words

Integrity gaps

Lists of questions

Some niche benchmarks

Run a trial

Benchmarks that industries care about

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

Detailed success/failure case studies

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

Find the fuzzy-power words

Integrity gaps

Initial ML system

mental picture

Lists of questions

Some niche benchmarks

Run a trial

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

Benchmarks that industries care about

AI/ML best practices (by industry?)

Detailed success/failure case studies

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

' |

Initial ML system mental picture

Find the fuzzy-power words

Integrity gaps

Lists of questions

Some niche benchmarks

Run a trial

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

Benchmarks that industries care about

AI/ML best practices (by industry?)

Detailed success/failure case studies

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



Thanks!

