



P i s c e s

# Steve

Investor



Meet Steve.

Steve wants to harness the power of AI  
to make informed investment decisions.

# Steve

Investor



...but he struggles with...

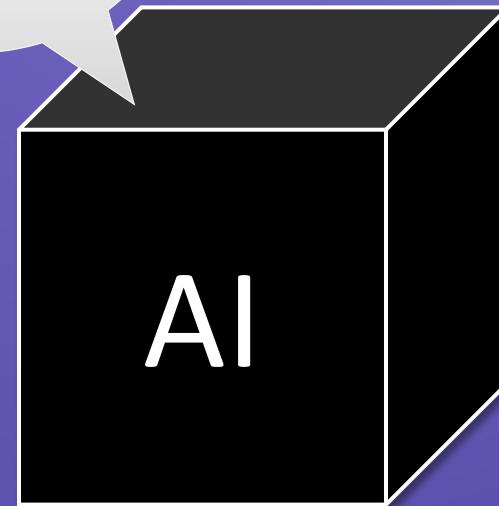
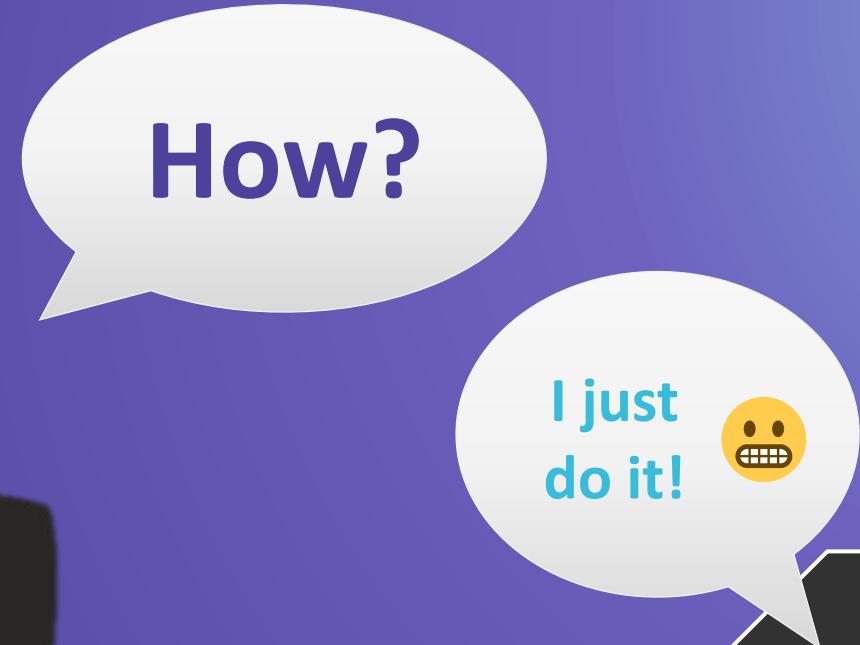
Filtering relevant information.

Utilising AI prediction models.

Trusting model performance.

Even when he can, he doesn't understand the results.

**Steve**  
Investor



**99%**  
Model Accuracy

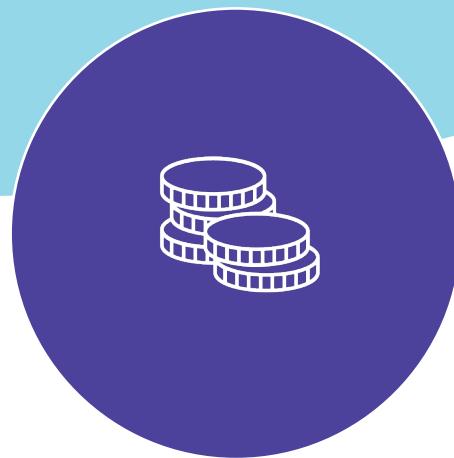
# Pisces opens the AI Black-Box for Investors



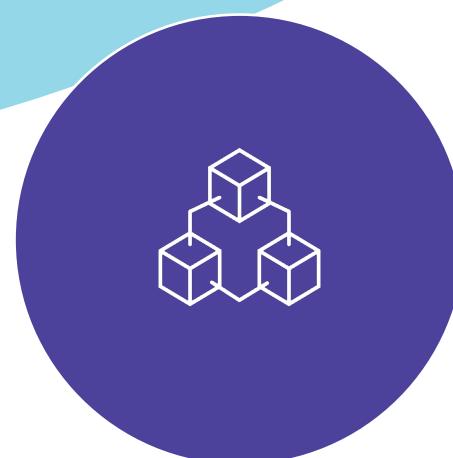
Actionable  
Investment **Insights**



Driverless  
**AI Interpretations**

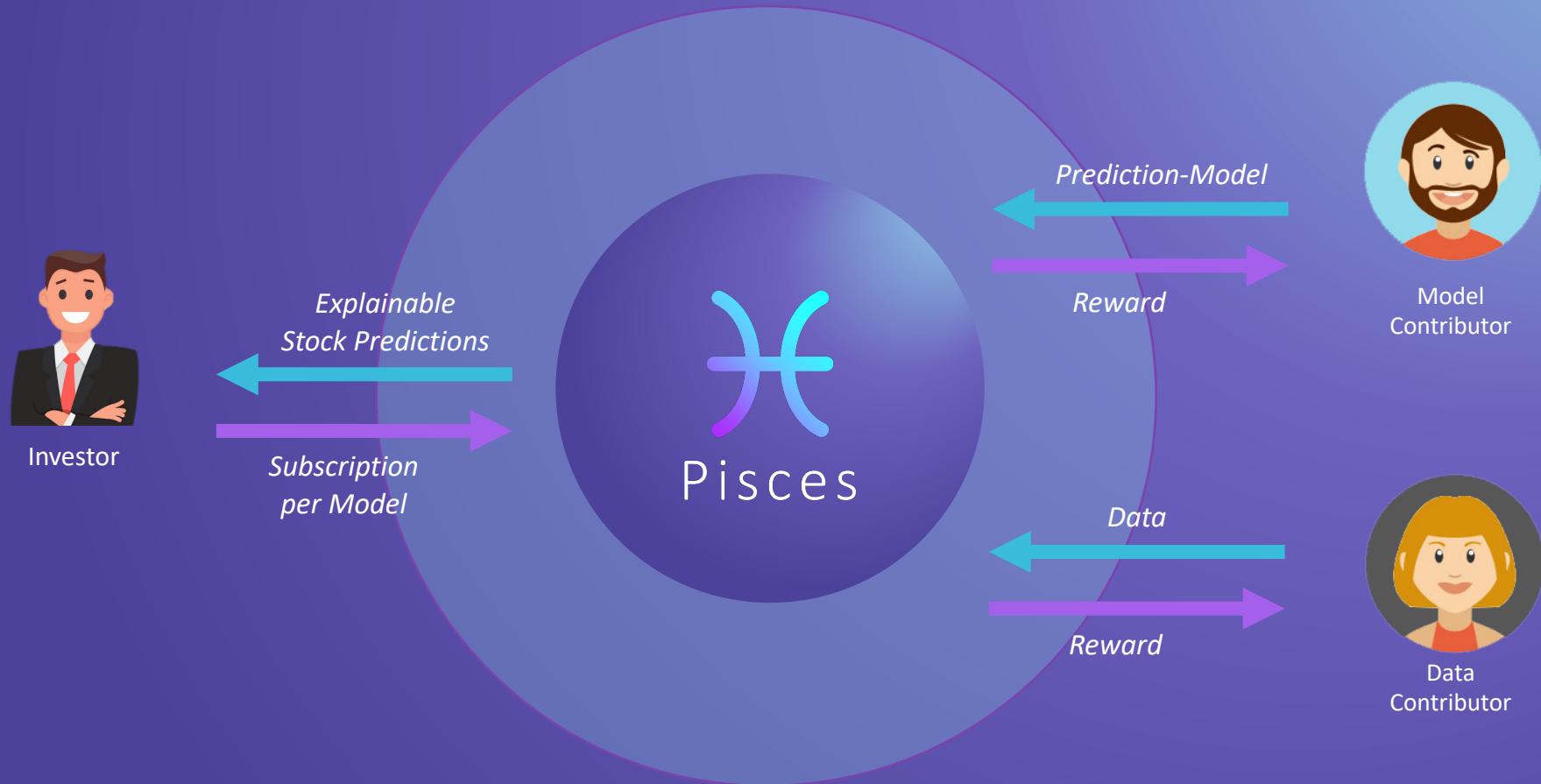


**Marketplace for**  
Prediction Models



**Blockchain-based**  
Model Performance  
Tracking

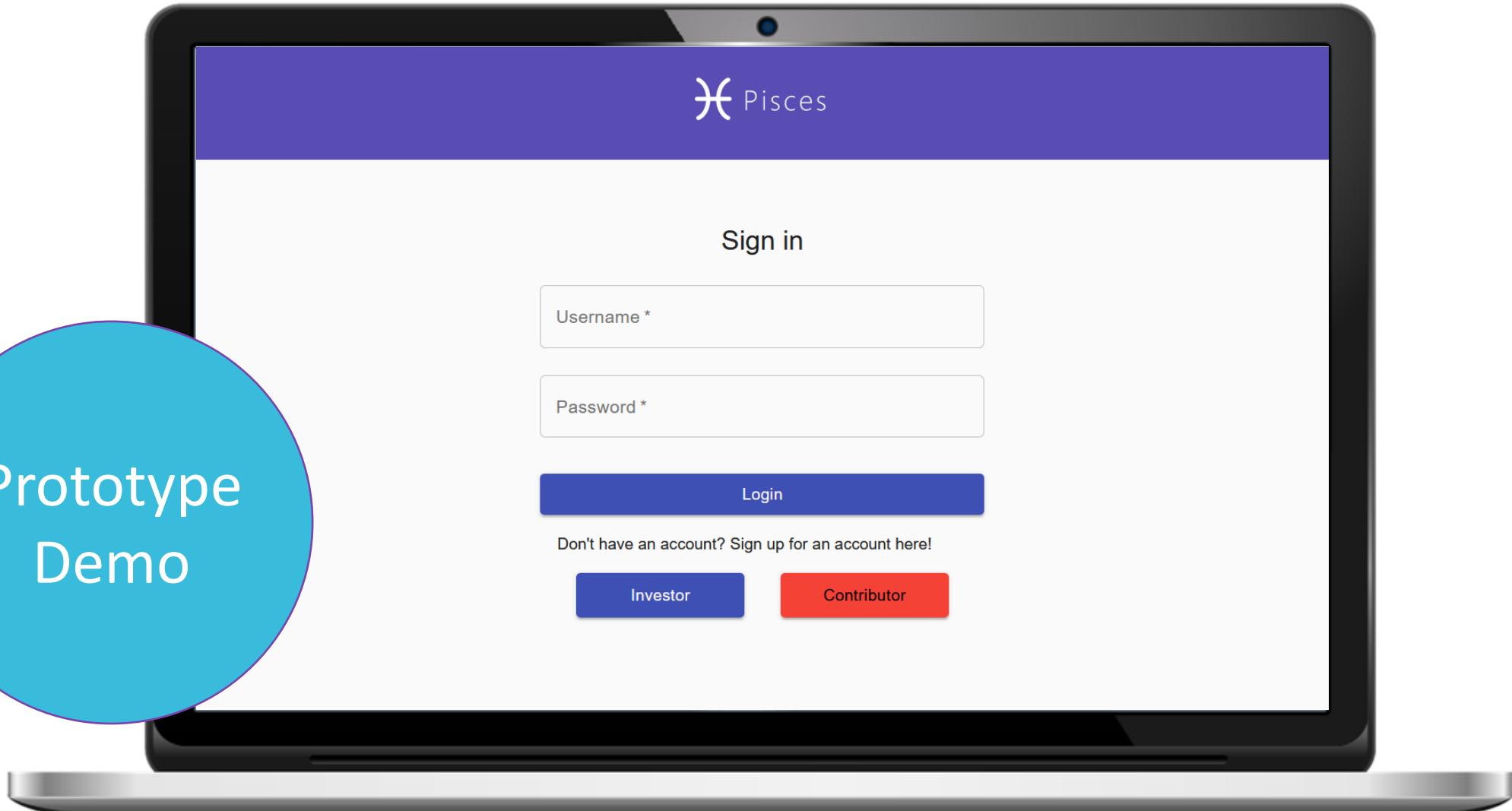
# Subscription-based Business Model



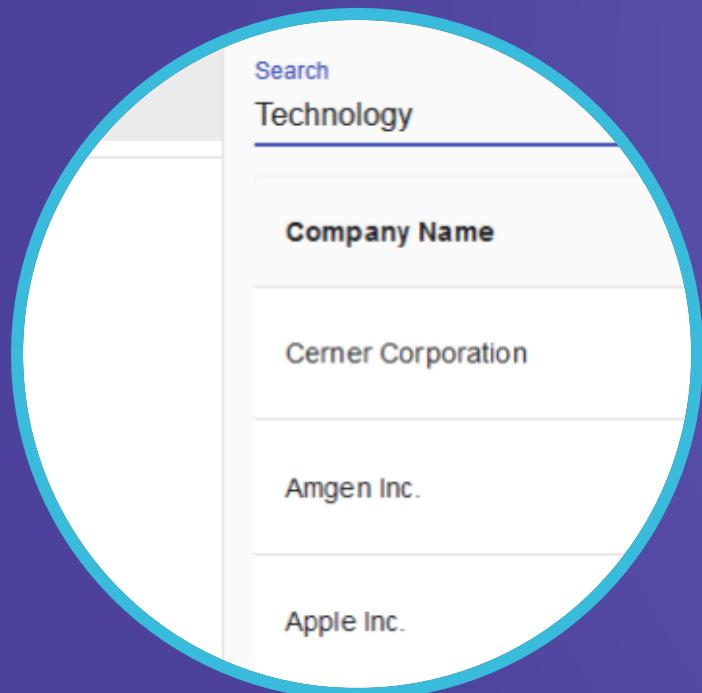


# Investor's Experience

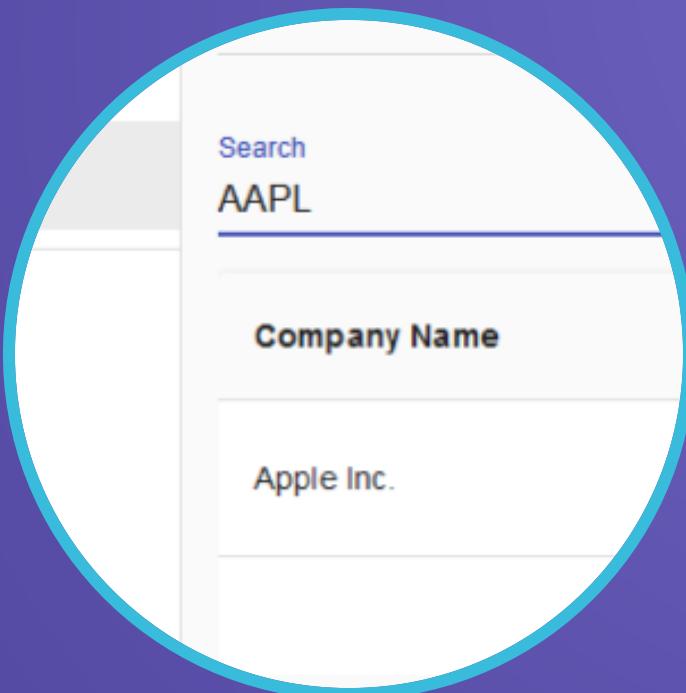
Prototype  
Demo



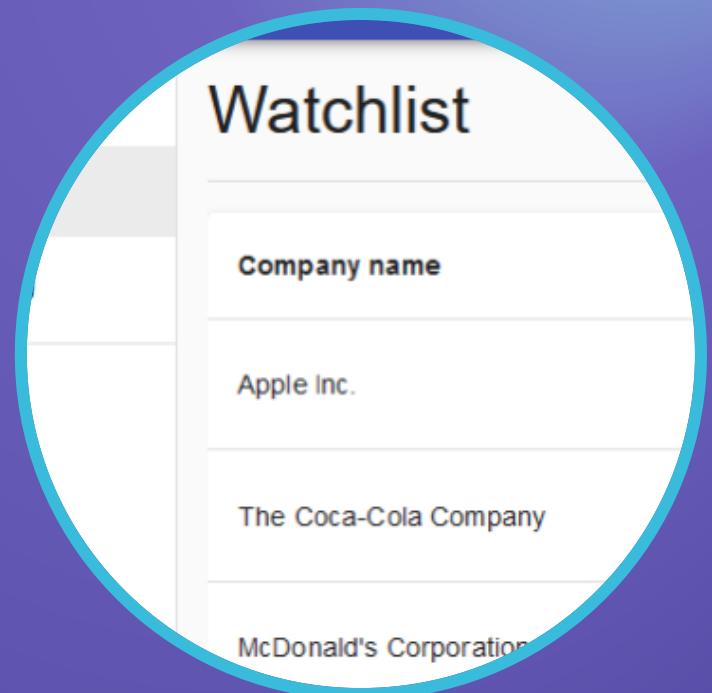
# Stock Screening



Screen Industries



Search Stocks

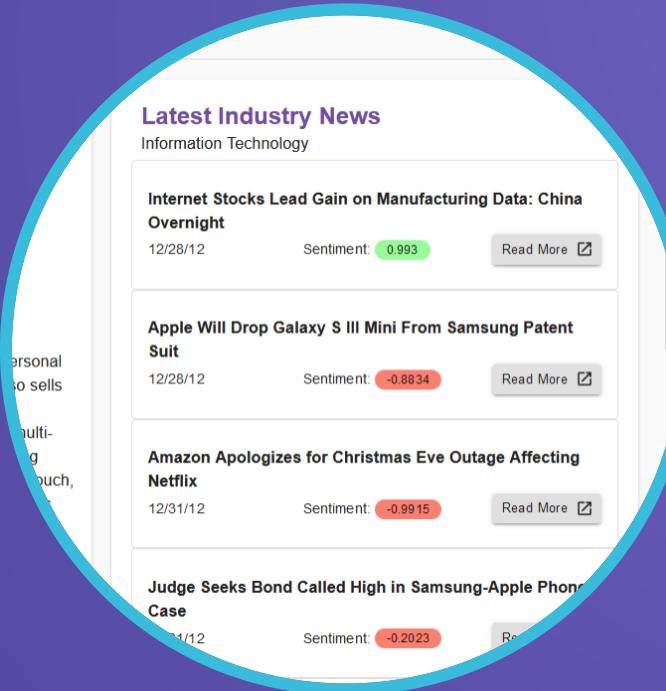


Add to Watchlist

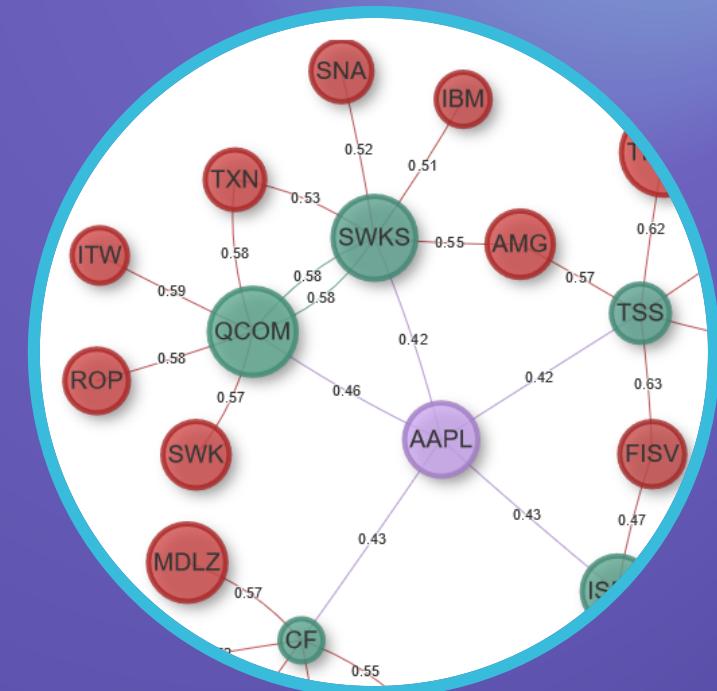
# Company Insights



Review Key Statistics



See Market Sentiment



View Company Relations

# Prediction Models

### Top Performing Models

# 1	<b>Time Series Random Forest v1</b> Kenny · $R^2 = 0.71$
# 2	<b>Jacked Ensemble Aggregator</b> Tommy Top Gun · $R^2 = 0.65$
# 3	<b>ZTS-37</b> Mr Zhang · $R^2 = 0.63$
# 4	<b>Bae-st-sell</b> Alex Baesell · $R^2 = 0.58$
# 5	<b>RegressionAggression</b> Wenpsy · $R^2 = 0.51$

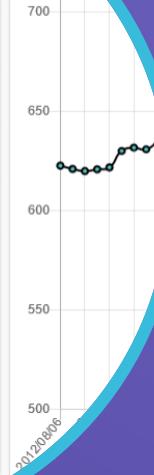
Select a Model

### Time Series Random Forest v1

Model ID	1001
Author	Kenny
Stock	AAPL
$R^2$	0.71
Uploaded at	01/10/2012

A random forest tree regression model trained on lag-3 days closing price, industry news sentiment score distributions, and financial indicators and relevant metrics. Harnessing the power of natural language processing for news article topic modelling, and sentiment analysis using transfer learning.

Verified Model- predictions on the blockchain ledger has been verified. (Click to view ledger)



View Performance

### Verify in Blockchain

(SHA256)	FC73B890F91DD8E92C402A45FA57E89DF7E26770117
Date	27/12/2012
Model	Time Series Random Forest v1
Author	Kenny
Stock	AAPL
Today Actual	\$515.06
Next Day	31/12/2012
Next Prediction	\$513.81

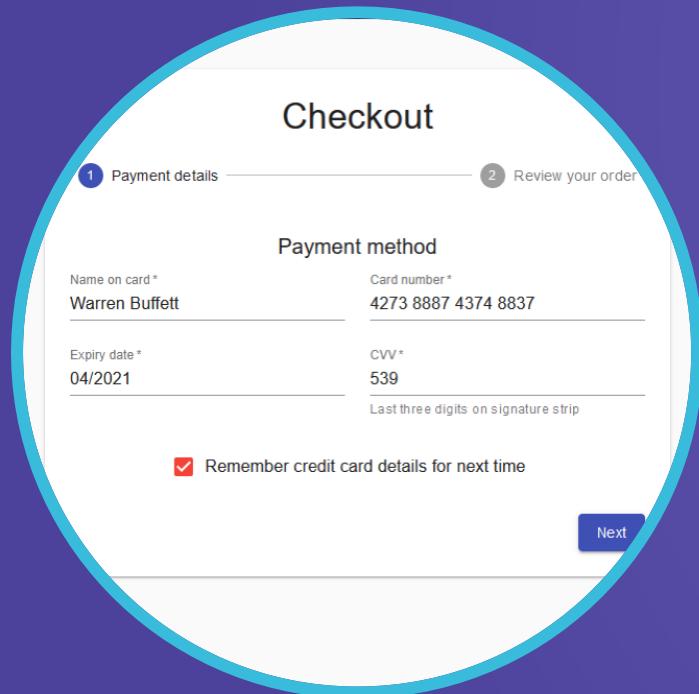
  

Hash (SHA256)	A6E04AB59886247D70BC8C798A454108342CF134A0727DEB61
Date	26/12/2012
Model	Time Series Random Forest v1
Author	Kenny
Stock	AAPL
Today Actual	\$512.99
Next Day	27/12/2012
Prediction	\$509.71

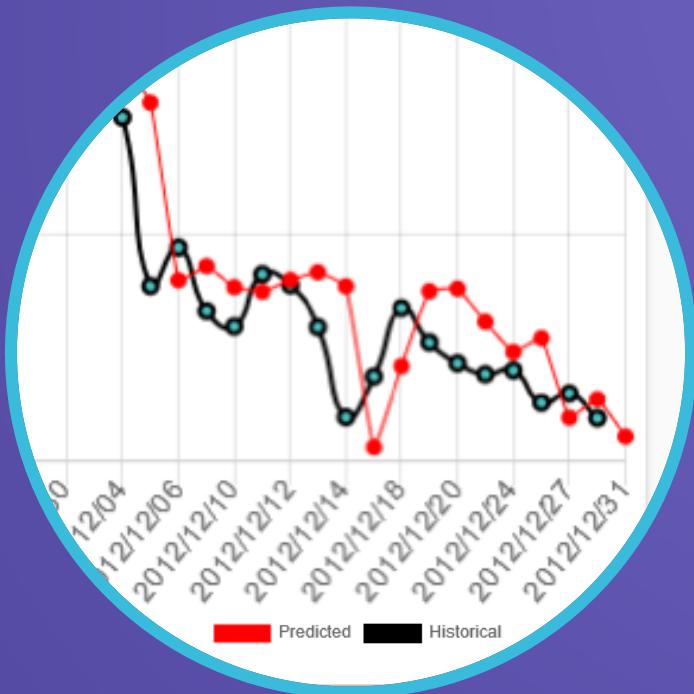
47D700AC61B652FE31D70050159AF973185

Verify in Blockchain

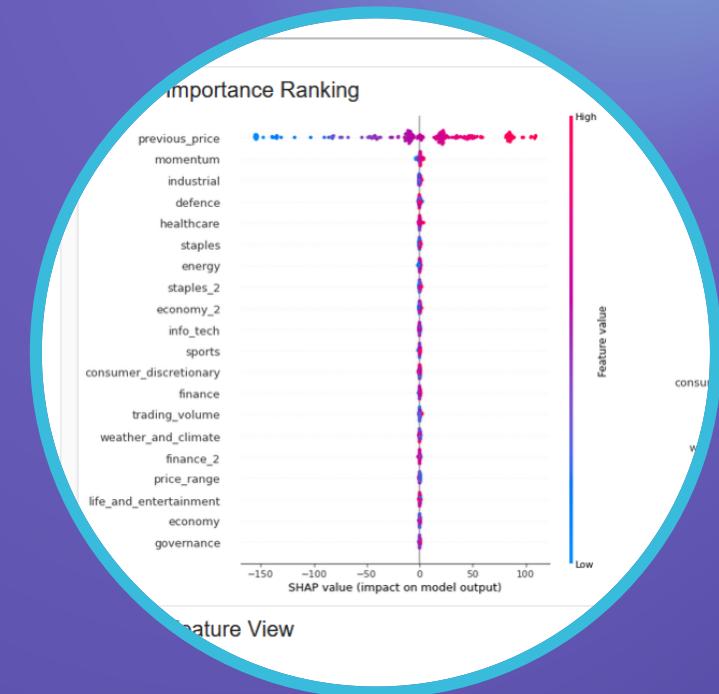
# Stock Prediction and Interpretation



Subscribe Model



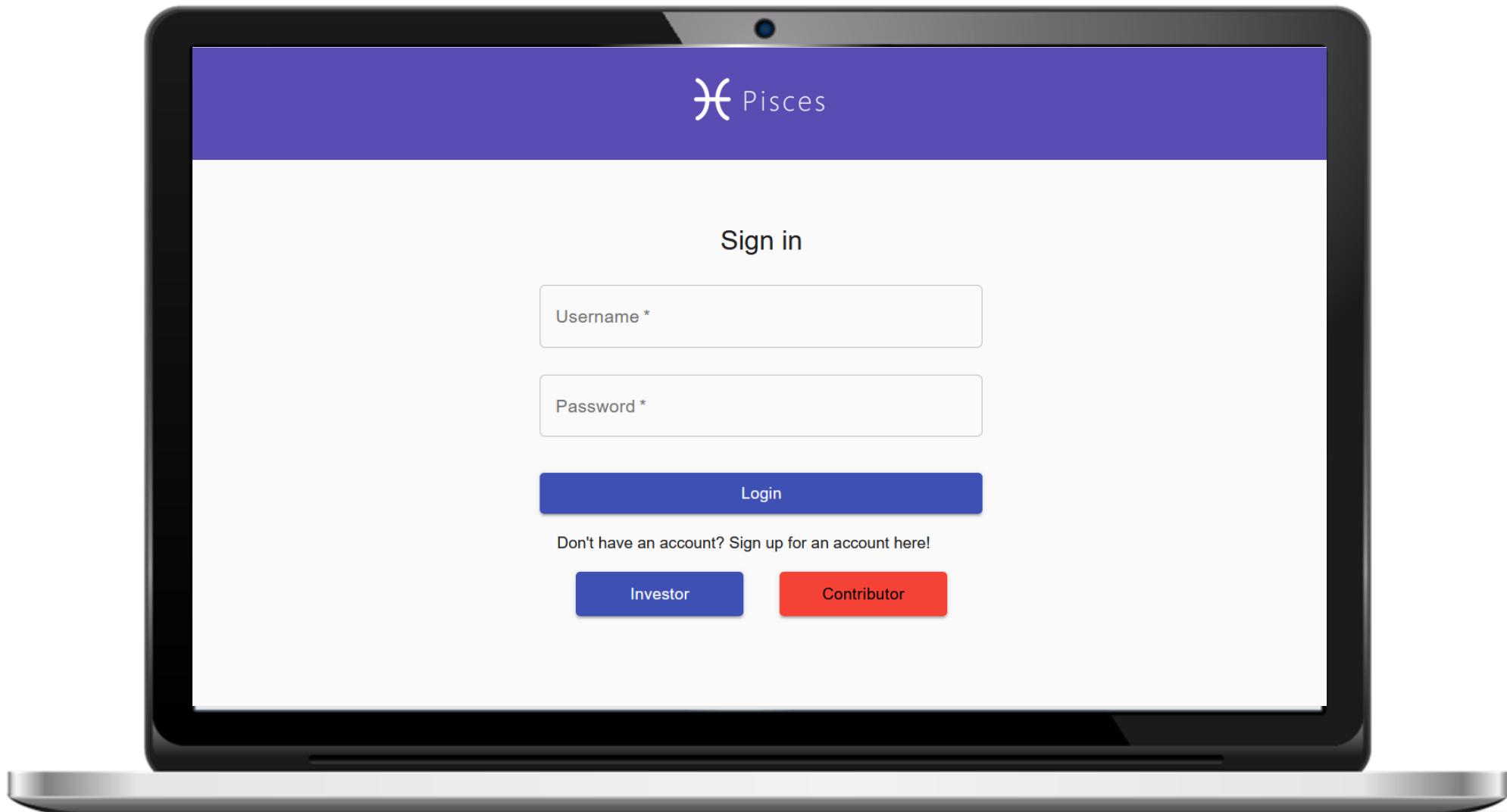
View Prediction



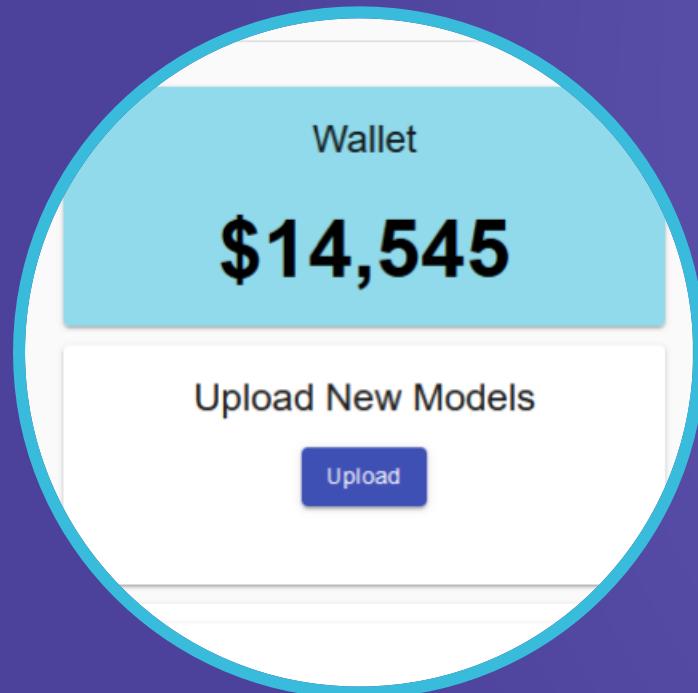
Interpret Model



# Contributor's Experience



# Contributor's Features



Upload Model

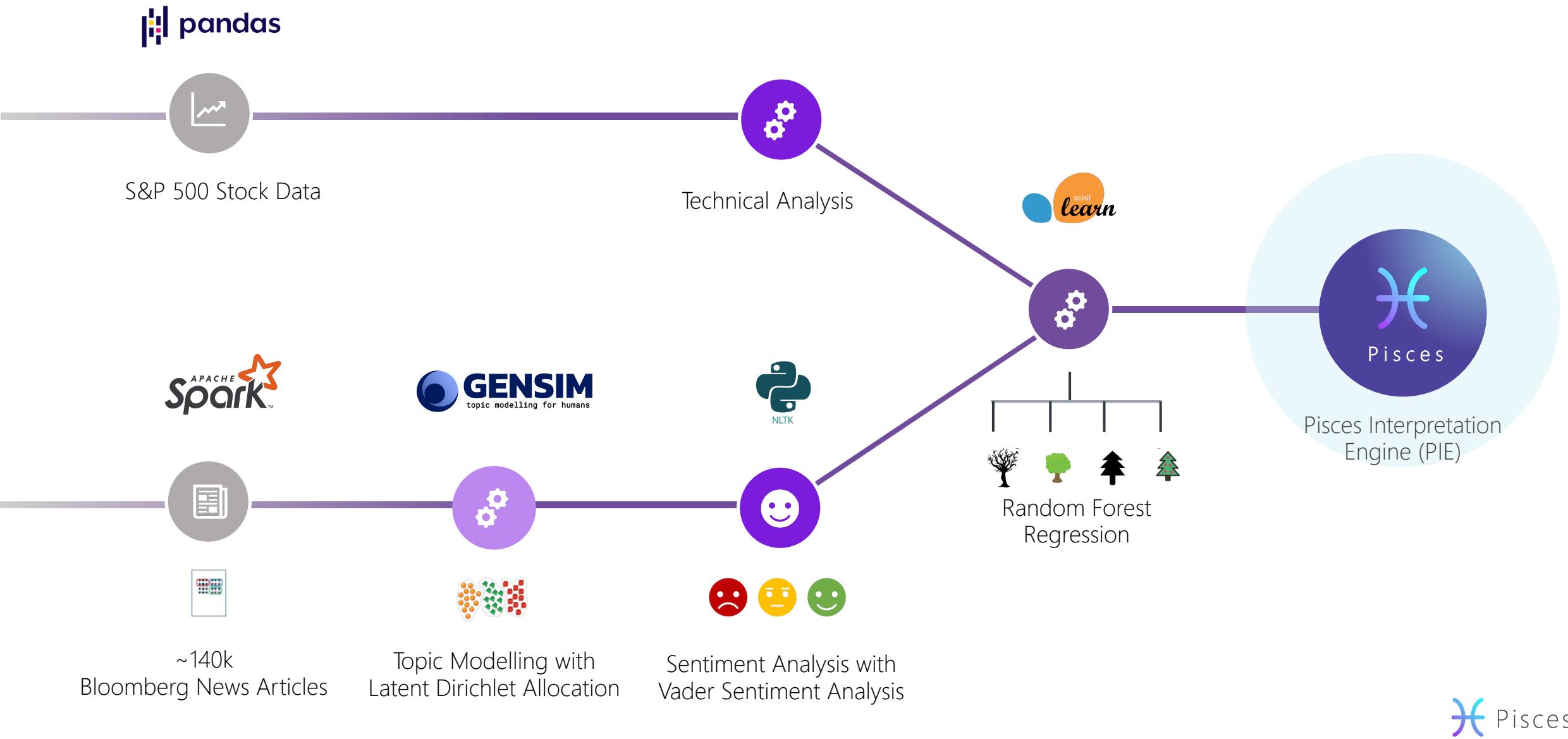
Model Rankings	
Model	ranking
Time Series Random Forest v1 [AAPL]	#3
TSPC-372 [MSFT]	#27
You-r-0.679 [AMGN]	#18

View Model Rank

Feedback	
Perhaps that it will be more useful when you consider this strategy with fundamental analysis	Updated 2 hours ago
This is exactly what I needed. Great Job!	Updated 2 hours ago
The interpretability of the model is really helpful and make me a better investors, two thumbs up!	Updated 3 hours ago
you also do models specifically for a tech	Updated 3 hours ago

Read Feedback

# Prediction Model Process Overview





# Technical Analysis

stock data



Daily Price Range



Market Volatility

Trading Volume /  
Market Cap



Stock Market  
Disagreement

Stochastic Oscillator

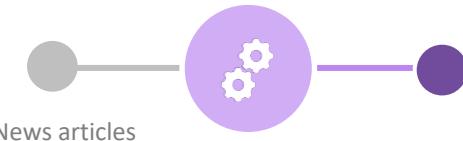


Price Momentum,  
Overbought, Oversold  
Signal

MACD, Signal Line,  
Crossovers

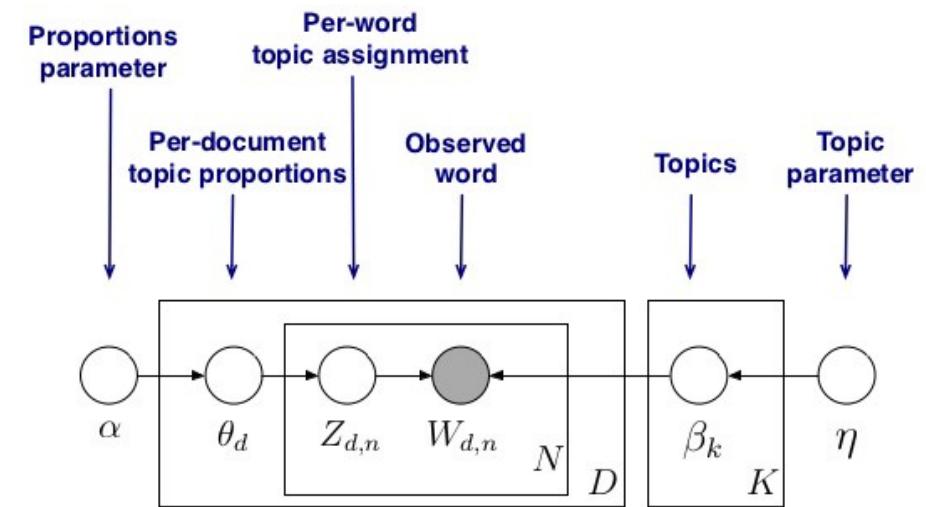
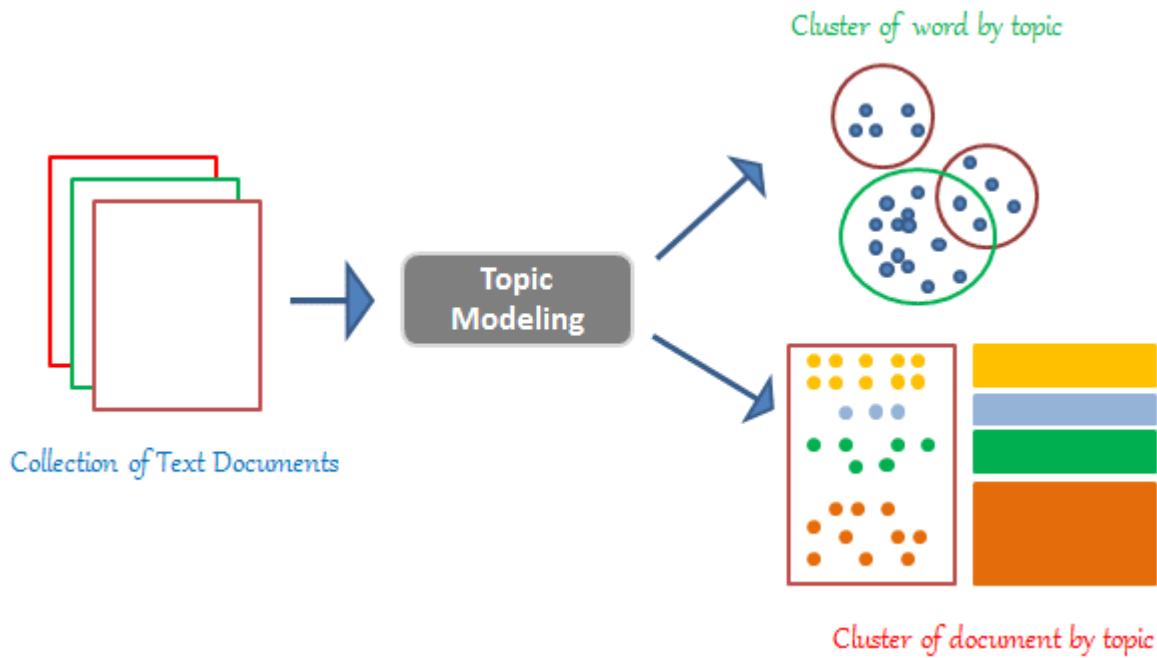


Possible Bullish,  
Bearish trend



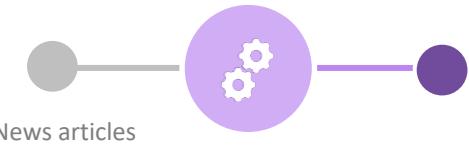
News articles

# Latent Dirichlet Allocation Topic Modelling

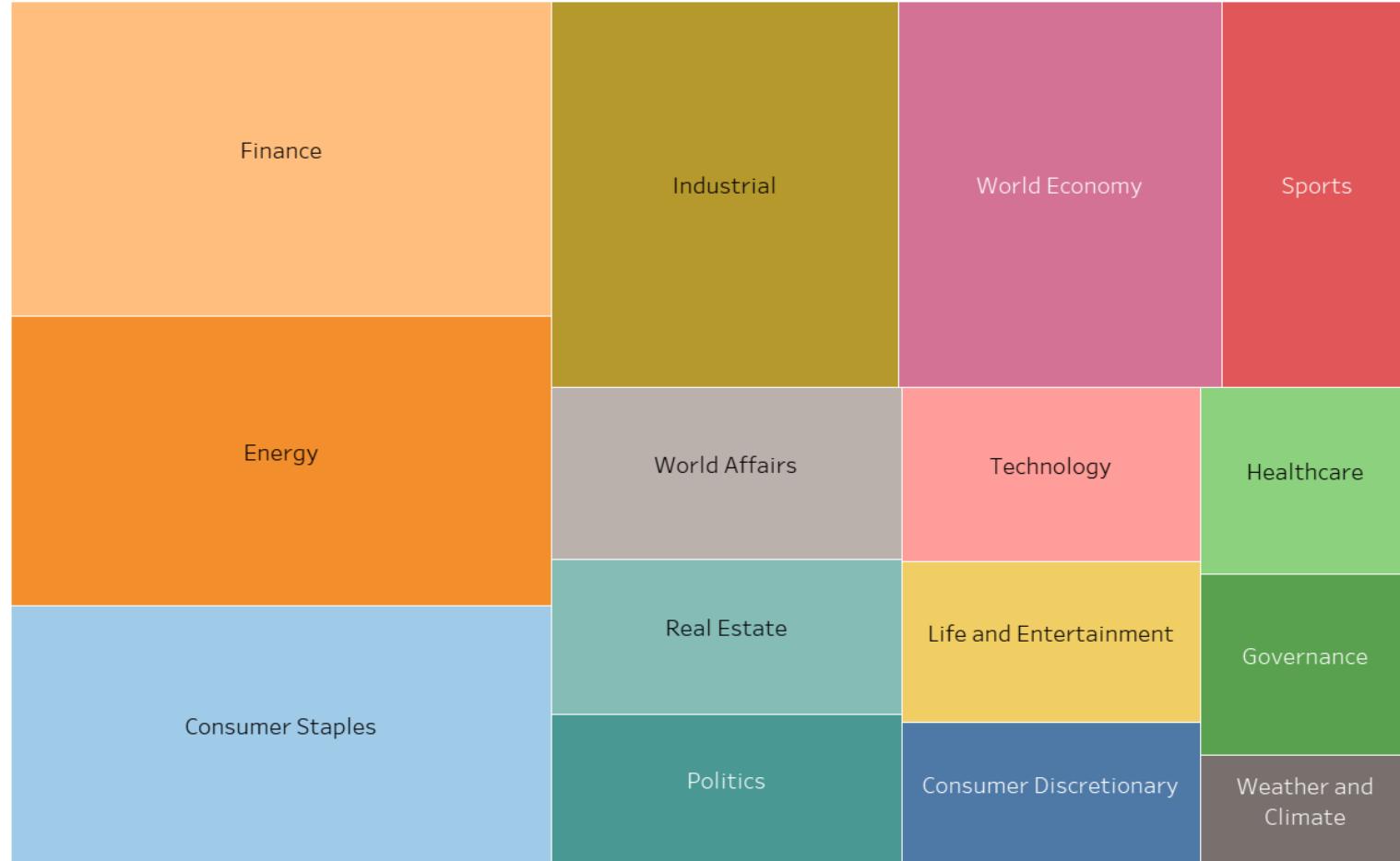


$$\prod_{i=1}^K p(\beta_i | \eta) \prod_{d=1}^D p(\theta_d | \alpha) \left( \prod_{n=1}^N p(z_{d,n} | \theta_d) p(w_{d,n} | \beta_{1:K}, z_{d,n}) \right)$$

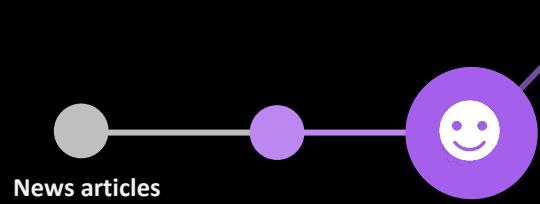
A probability distribution model that assumes similar words make up similar topics, and several topics make up a document.



# Topic Modelling Results



Distribution of Bloomberg News Articles by Topic in 2012



# Sentiment Analysis with Vader

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# Sentiment Analysis with Vader

- Sentiment analysis applied to Bloomberg news articles
- Valence-aware lexicon-based approach using a curated dictionary of word to sentiment scores
- Takes into account:
  - Punctuation
  - Capitalization
  - Degree modifiers

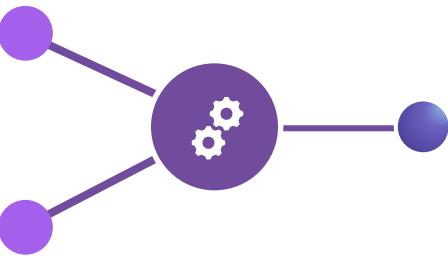
For Example:

"Swiss Exchange Trading Open **Delayed** Due to Unspecified Technical **Problems**"  
-0.4019  
-0.2263

[Overall Score: **-0.6452**]

"Swiss Exchange Trading Open **SEVERELY DELAYED** Due to Unspecified Technical  
**Problems!!!**"  
multiplier \* -0.4019  
multiplier \* -0.2263

[Overall Score: **-0.8733**]



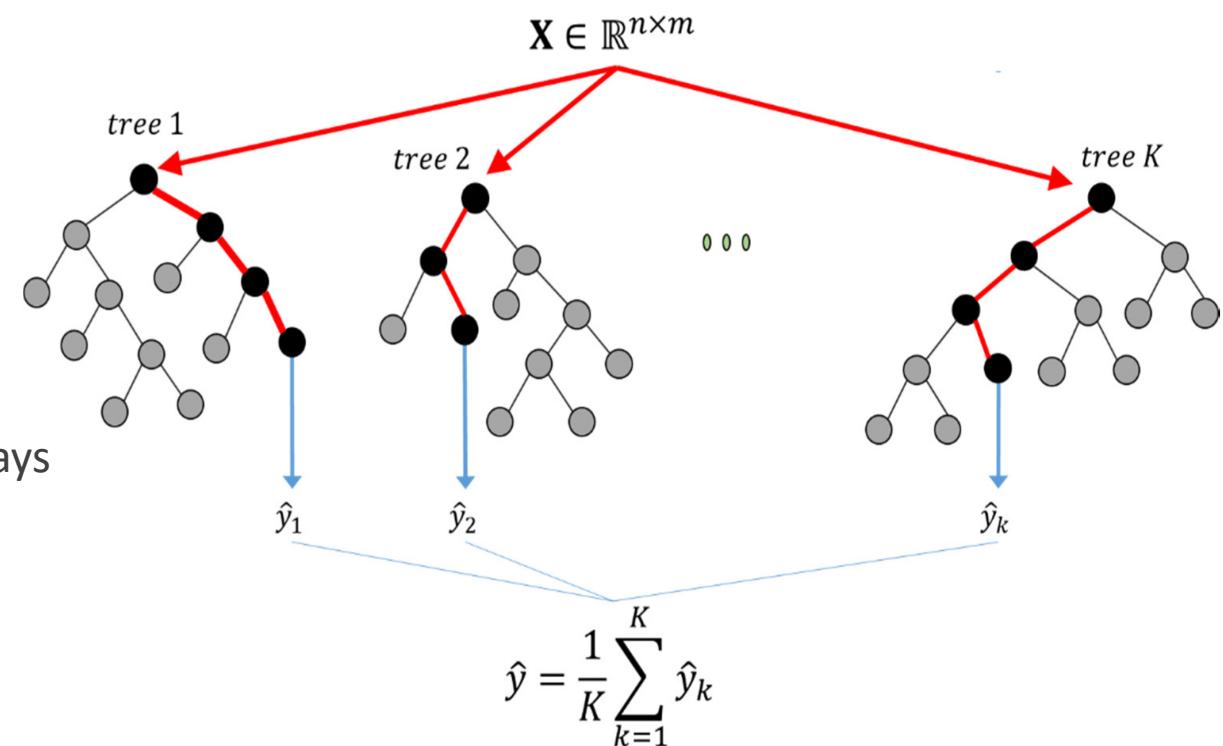
# Random Forest Regression

1. Relies on the **"wisdom of crowds"** approach to find an average prediction

2. Performs **bootstrap aggregation** on features and observations

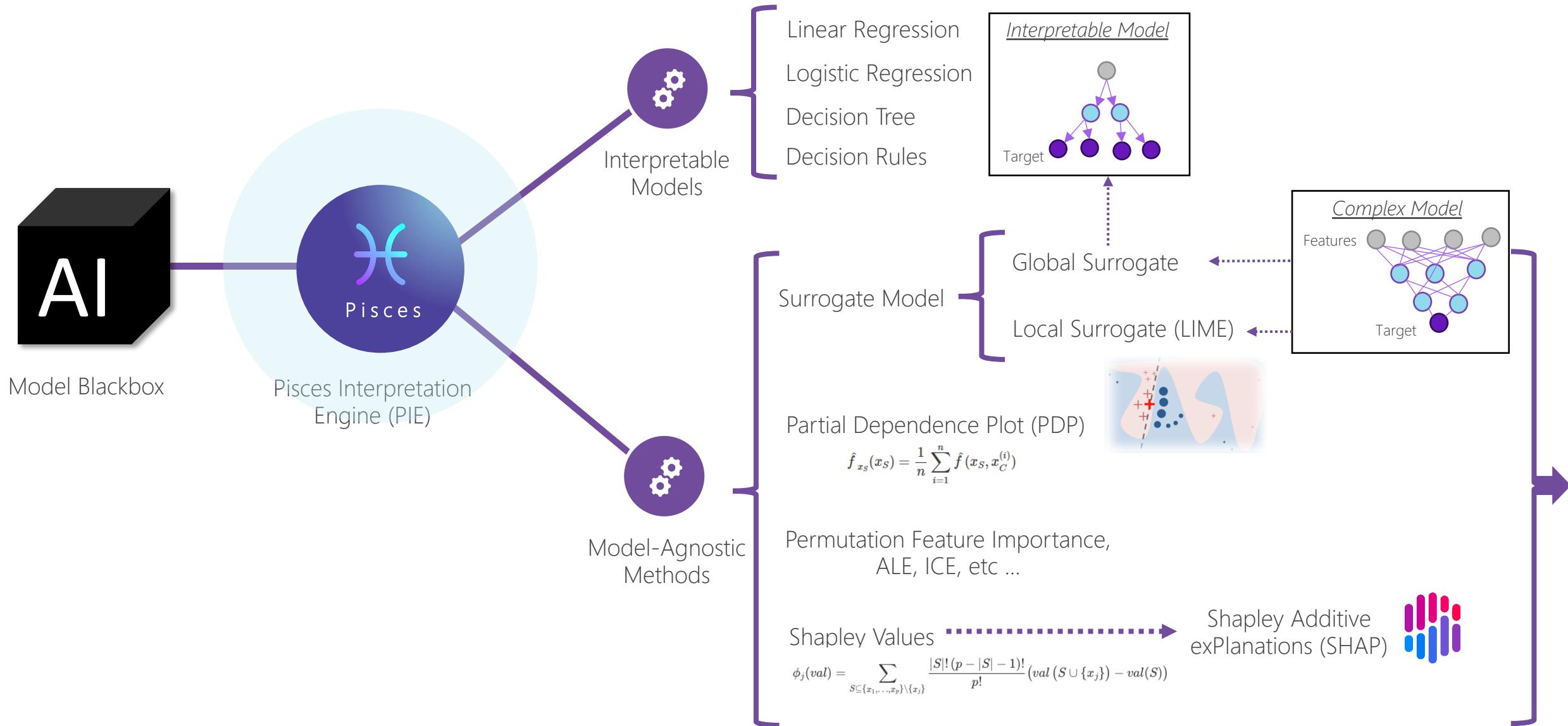
3. Features Used:

- **Technical Analysis Features** in the preceding 3 days
- Averaged **Sentiment Scores** Across Topics in the preceding 3 days
- **Stock price** in the preceding 3 days





# Pisces' Model Interpretation



# How Do Price Influencers Contribute Differently In General?



SHAP

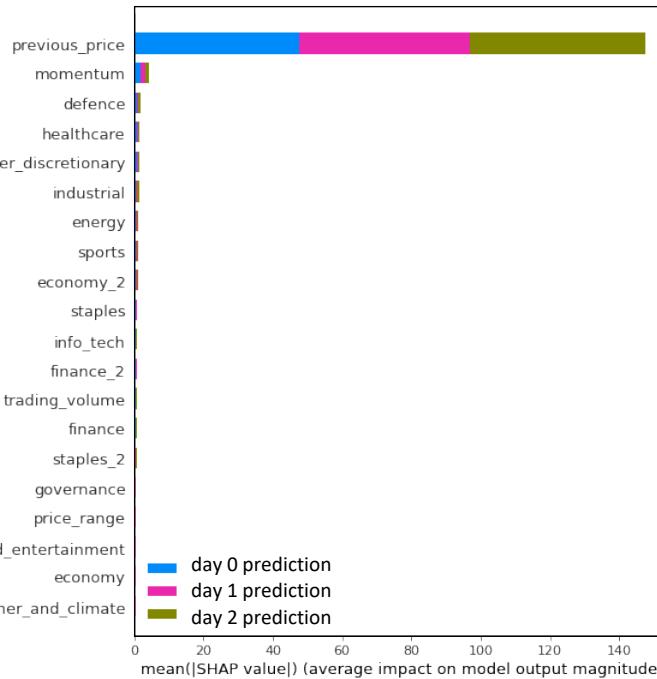
Top price  
influencers  
are ranked  
by  
importance.

High  
Impact

Low  
Impact

## Bar Plot

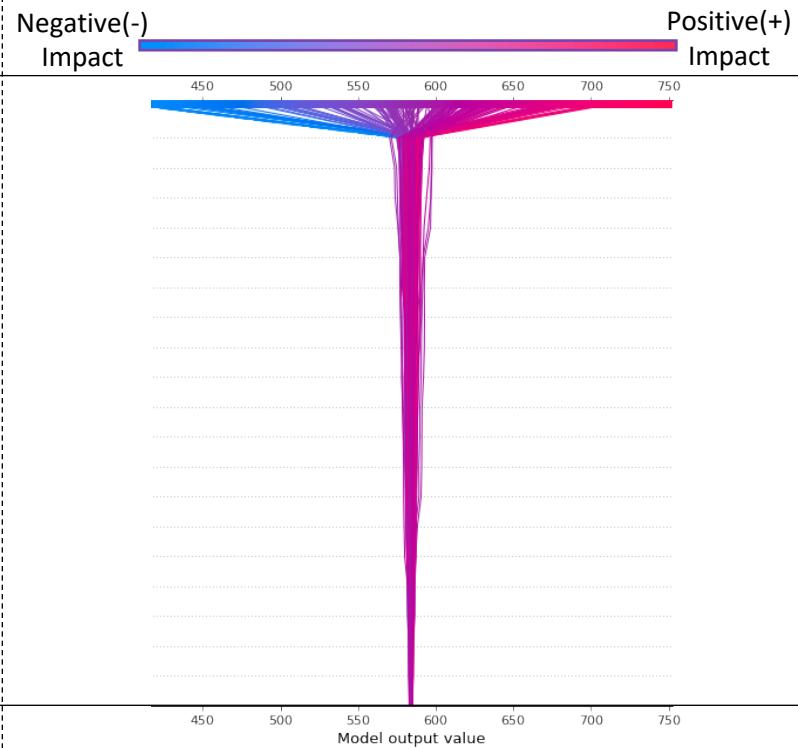
- Horizontal axis: **Population Average SHAP Value**
- Vertical axis: **Feature Ranking**
- Compares the total feature impact on predicted day 0, day 1 and day 2 price**



## General Feature Ranking View

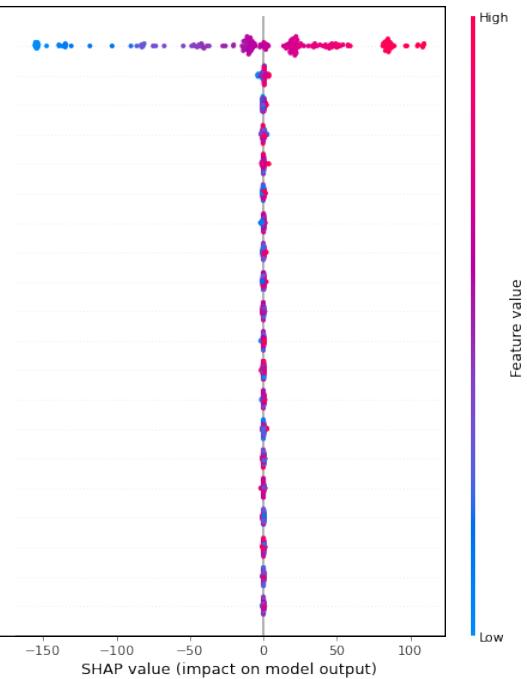
## Decision Plot

- Horizontal axis: **Price**
- Vertical axis: **Feature Ranking**
- Shows how model accumulates features' impact and arrives at prediction step by step**



## Beeswarm Plot

- Horizontal axis: **SHAP Value**
- Vertical axis: **Feature Ranking**
- Shows how the relative impact of each feature is distributed across observations**



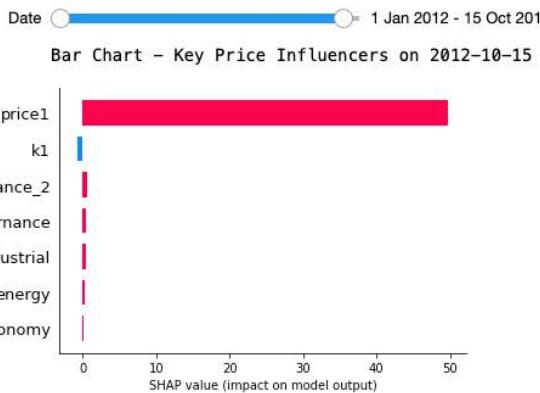
## How Do Features Impact Price For a Given Day?

## How Does Price Respond To A Specific Feature?

### Specific Day View

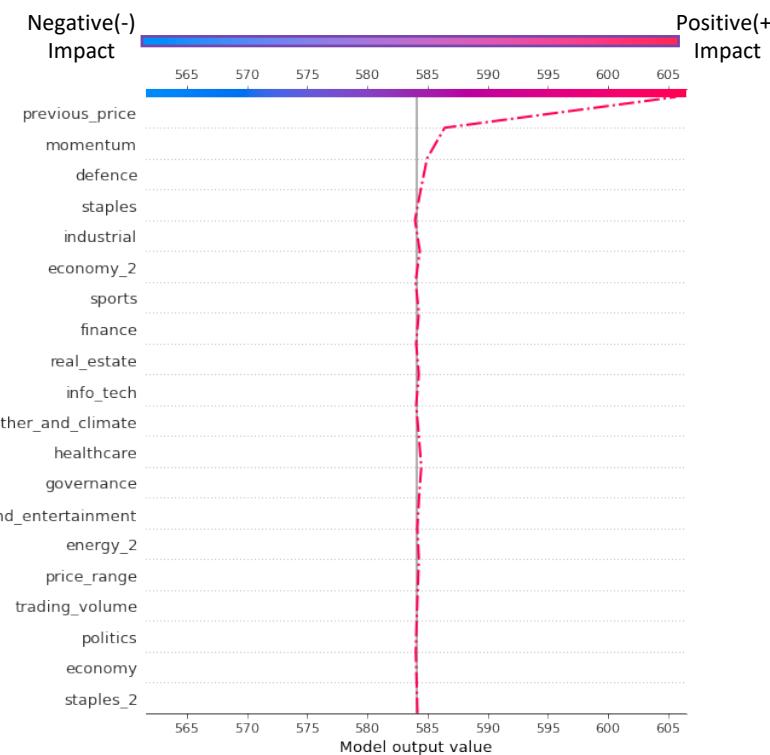
#### Bar Plot Slider

- Horizontal axis: **SHAP Value**
- Vertical axis: **Key Feature Ranking**
- **Compares relative feature impact on a date chosen by user**



#### Decision Plot

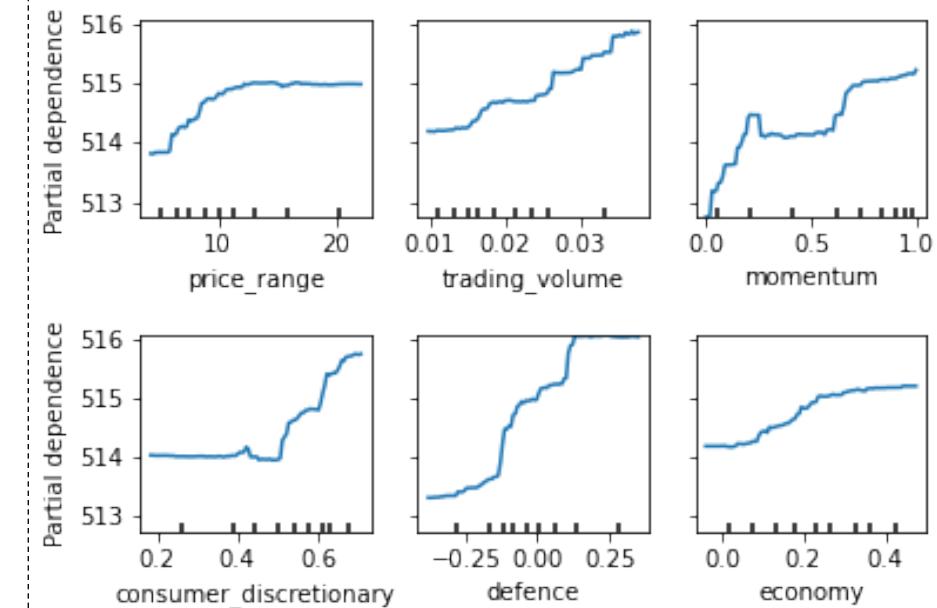
- Horizontal axis: **Price**
- Vertical axis: **Feature Ranking**
- **Shows how model accumulates features' impact and arrives at prediction step by step**



### Specific Feature View

#### Partial Dependence Plot

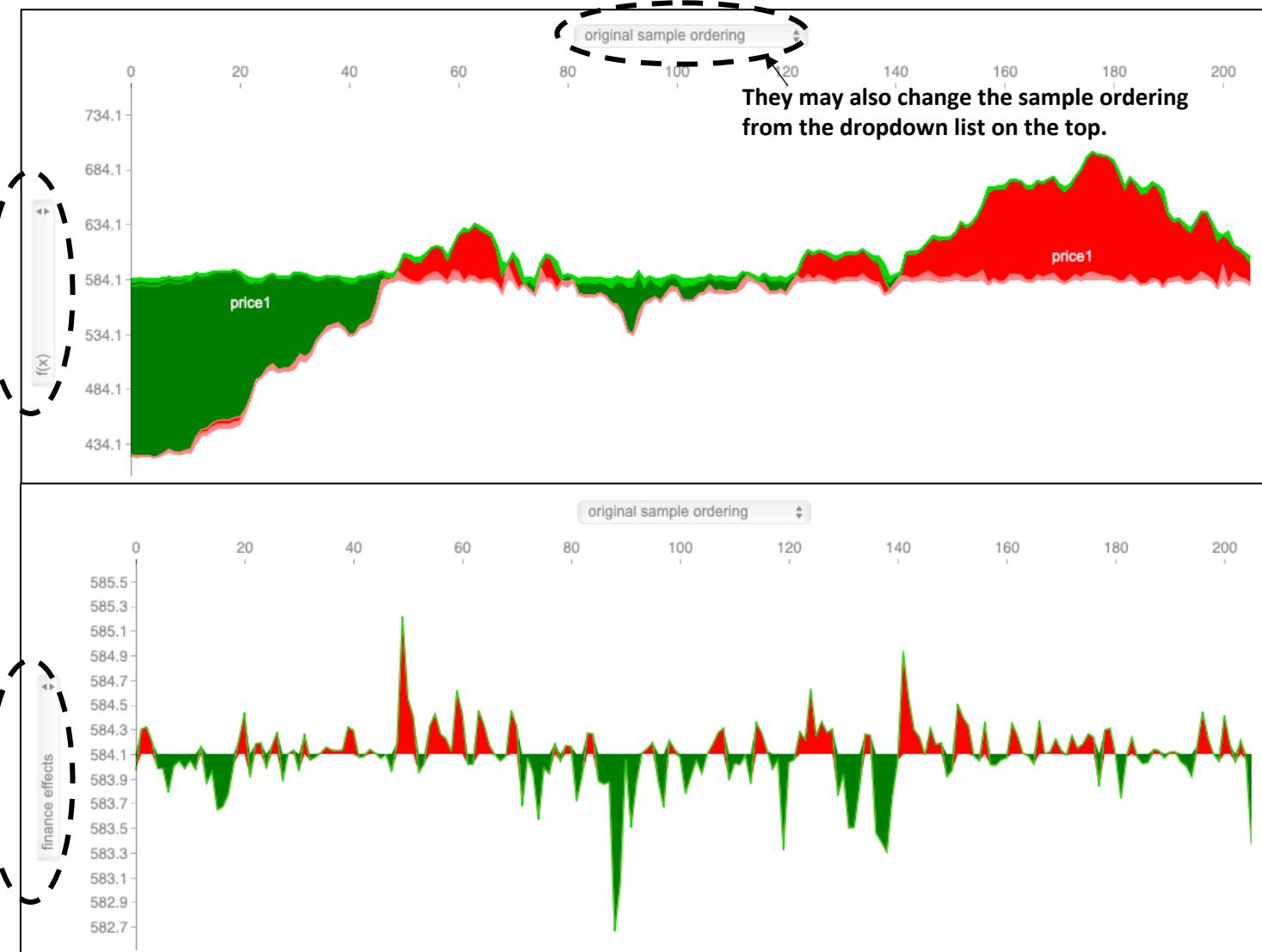
- Horizontal axis: **Feature Value**
- Vertical axis: **Price**
- **Shows how price responds to individual feature in absolute correlations**



# How Do Features' Contribution Change With Time?

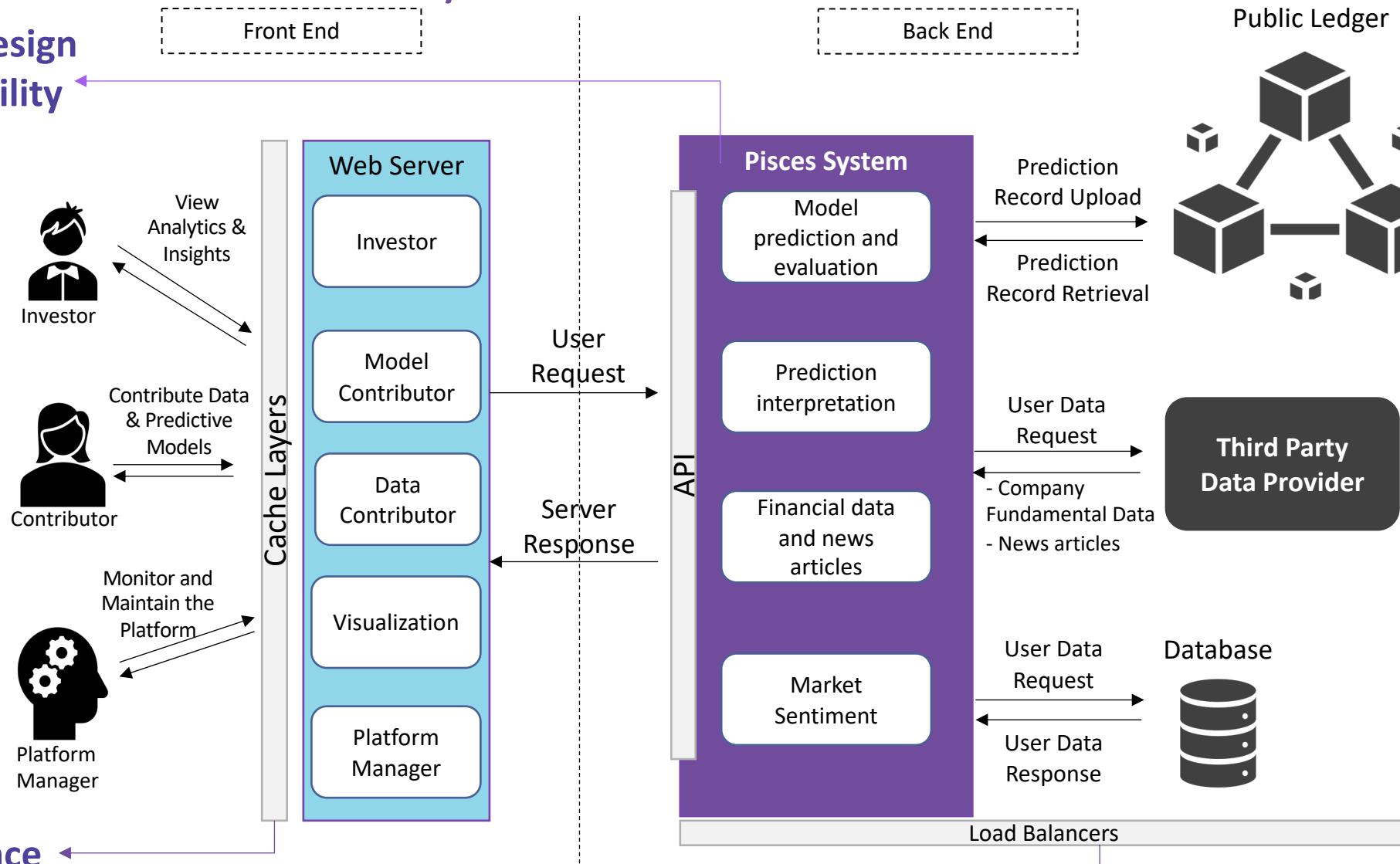
## Price Movement with Time Interactive View

- Horizontal axis: **Observation Count, i.e. Date**
- Vertical axis: **Feature Ranking**
- Allows users to view how relative contribution of price influencers on price change across days
- **Users can use the dropdown list on the left to choose which feature they want to investigate.**



# System Architecture

Modular Design  
- Modifiability



Trust

Performance

Reliability &  
Scalability

# Win – Win - Win



**Investor**

Access to a range of models with **explainable** predictions

**Trusted** model performance through blockchain proof

Pay per **model subscription**



Margin on model subscription enables **sustainable revenue**

**Low risk business model**



**Contributor**

**Monetisation** of data and prediction models

**Transparent evidence** of model performance

**Immutable proof** of data and model ownership



**Drive ML adoption  
for financial industry**



**Enable collaboration  
through capitalisation**



**Protect originality  
and build trust via  
Blockchain ledger**

# Thank you!



Alexander  
Baesell

Liow  
Jia Chen

Ken  
Cheah

Tommy  
Kangdra

Yu  
Wenxi

Zhang  
Tongsen