



# *Data Driven Method in Finance*

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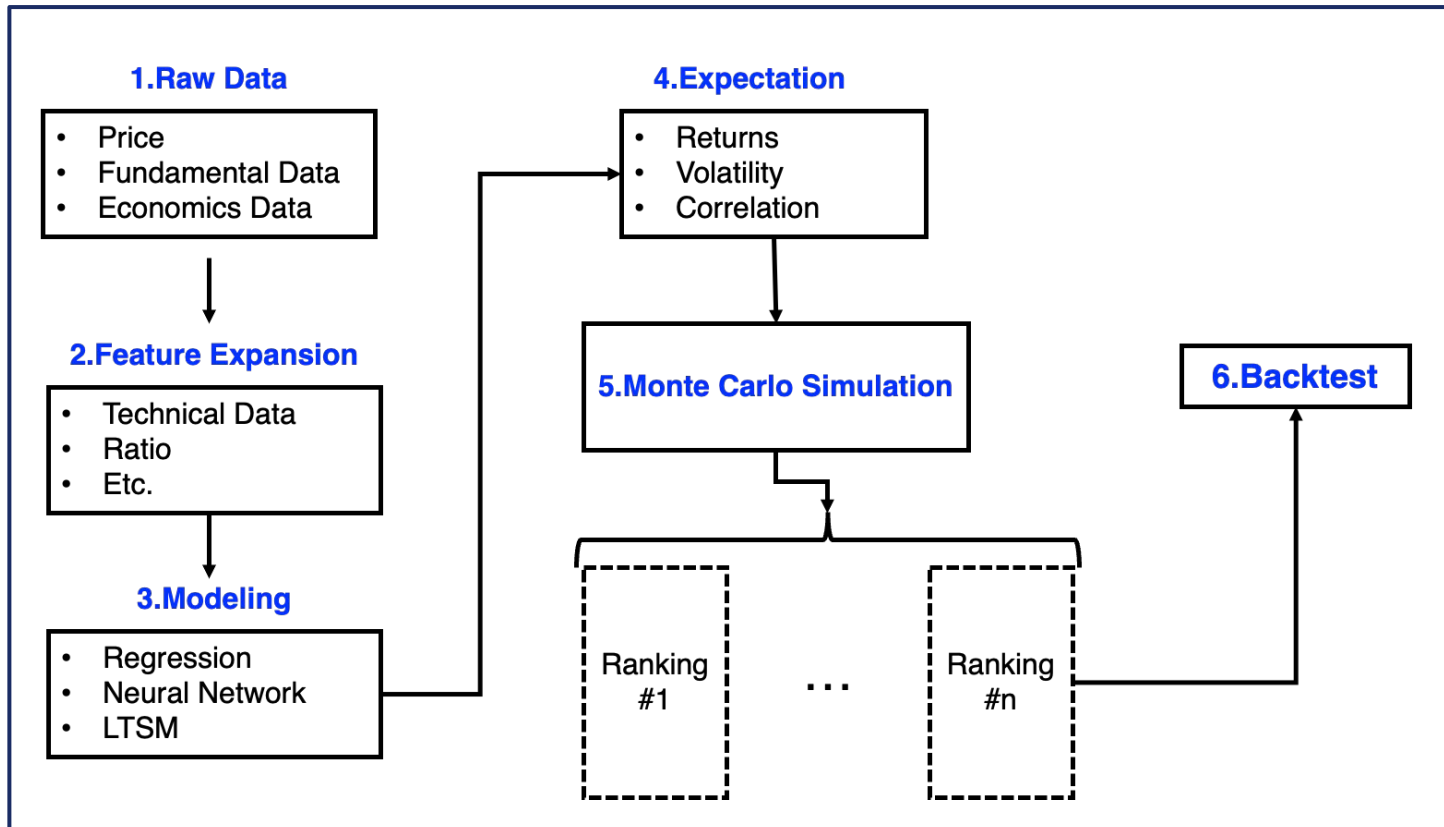
TRANSCENDING DISCIPLINES, TRANSFORMING LIVES

# Agenda

- Our Approaches - 2
- Data - 1
- Model and Methods - 1
- Week to week flow of data - 1
- Results - 2
- Lesson Learned - 2

# Approach (1/2) - Initial Approach

- Our goal is to build a **framework** that will ensure **robust performance** and **streamlined** our ideas into quantitative decision
- We then divided the framework construction into multiple modules. As shown below



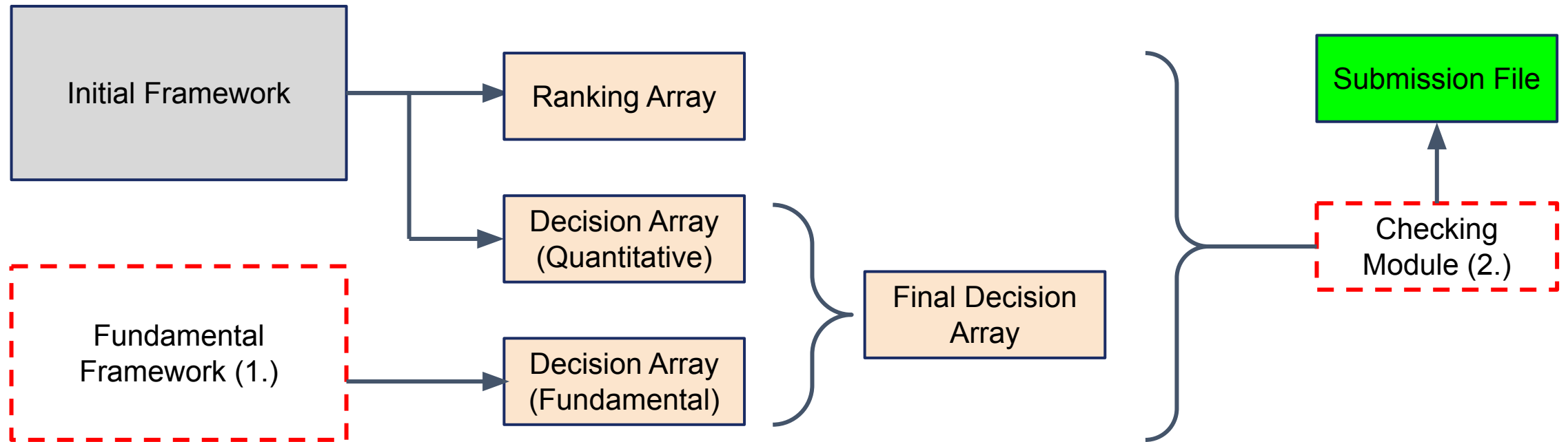
## Key component in Each Module

1. **Raw Data** - Get Data from from openbb, FRED, and yahoo finance
2. **Feature Expansion** - python Technical Analysis Library
3. **Modeling** - XGBoost
4. **Expectation** - manually adjusted through python and csv file
5. **Simulation** - Through python
6. **Backtest** - Through python

# Approach (2/2) - Implementation

As competition went on we made 2 improvement to the initial implementation

1. We add fundamental approach module to the framework - to express view that is harder to express quantitatively
2. Adding Checking Module at the end of the pipeline
3. We wrap each module into python object for easier implementation



# Data

Our data came from 4 main sources each serving different dimensions of market view:

1. **Yahoo Finance**: for security prices and fundamental data
2. **FRED**: for macroeconomic data
3. **Estimize**: for trading earnings
4. **OpenBB**: for high level data ex. sentiment + insider trading

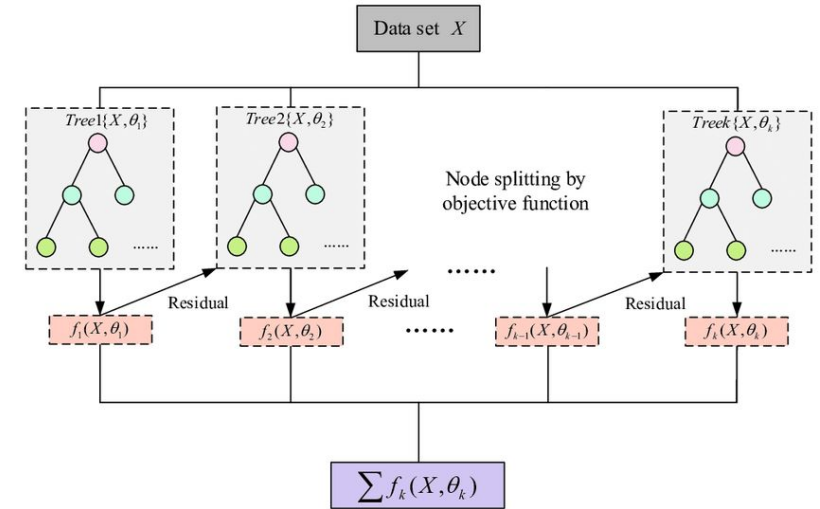
Overall, our size of features amounted to **427 features** for each asset

# Model and Methods

- At first we start modeling expected returns using various ranges of single models. These include:
  - Linear Models: OLS, Ridge, Lasso
  - **Support Vector Machine** - this being the one that gives us the best results
  - Decision Trees
  - Neural Network Model
- **Then we move toward ensemble methods:**
  - Bagging
  - Random Forest
  - AdaBoost
  - **XGBoost** - this being the best performing one

**Thus, our main modelling engine is based on XGBoost model**

## XGBoost Model



Pros:

- Works well with large dataset
- Resilient and Robust Results

Cons:

- Black Box Nature - Hard to interpret
- Model is sensitive to outliers



# Week to week flow

## 1. Import Related Module and Object

```
from Colab.code_base.data_utils import GetHistoricalData
from Colab.code_base.rank_simulator import RankSimulator

universe_df = pd.read_csv('data/universe_oct.csv')
```

## 2. Load Data via **GetHistoricalData** object

```
## Getting Historical Data
hd = GetHistoricalData(universe_df)
weekly_ret,daily_ret = hd.get_return_data()
hist_rank = hd.get_historical_ranking()
```

## 3. Read Loaded Data

```
## Read Fundamental Data
single_stock_data = pd.read_csv('data/single_stock_Data.csv',index_col=0)
x = single_stock_data.sort_values('TotalScore')
top_r_name = x[x['sector'] != 'Communication Services'].dropna().index[:10].to_list()
bot_r_name = x[x['sector'] != 'Communication Services'].dropna().index[-10:].to_list()

## Read Forecast Data
return_forecast = pd.read_csv('Colab/guy_mu_dec2.csv',index_col=0)
top_name = return_forecast.iloc[-1].fillna(0).sort_values(ascending=False).index.to_list()
bottom_name = return_forecast.iloc[-1].fillna(0).sort_values(ascending=True).index.to_list()
```

## 4. Allocate Weight

```
## Allocate Weights by Variance
ivp_list = top_name[:10] + bottom_name[:10]
cov_today = daily_ret[ivp_list].cov()
ivp_weight = getIVP(cov_today)
```

## 5. Simulate Ranking via **RankSimulator** object

```
## Get Rank Array by Simulation
rs = RankSimulator(return_forecast.iloc[-1].fillna(0)/252,daily_ret)
fore_mean = rs.simulate_rank()
```

## 6. Check and Save file

```
submission_file[['rank1', 'rank2', 'rank3', 'rank4', 'rank5']] = np.array(fore_mean)

submission_file['decision'] = np.array(weights)
checks[submission_file]

# submission_dir = dir_+'submissions/dueSep11/'
filename = 'NullCapitalLLC'+ '__'+submission_time
submission_file.to_csv('submission/'+filename+'.csv')
print(filename)
```

# Allocation

For Fundamental Approach: We Long/Short top/bottom 10 asset based on score calculated from these fundamentals

- return on assets
- total cash per share
- forward PE
- recommendation means

In order to get the weights for each name, we use solver to construct minimum variance portfolio from long and short names



# Results

- The results outperform the EW benchmark with 50% of the time (70% if week 7-8 is valid)
- Outperforming S&P 500 70% of the time (90% if week 7-8 is valid)

	group_name	weekly_rank_1	weekly_rank_2	weekly_rank_3	weekly_rank_4	weekly_rank_5	weekly_rank_6	weekly_rank_7	weekly_rank_8	weekly_rank_9	weekly_rank_10	overall_rank
0	LionQuant	9.00	3.50	1.50	2.00	5.50	5.00	3.00	8.00	7.00	1.50	4.600
1	EW	5.50	5.00	2.00	7.25	5.25	2.75	4.25	4.50	6.50	6.25	4.925
2	NullCapitalLLC	1.00	1.00	4.50	3.00	5.00	3.00	13.00	13.00	1.50	6.50	5.150

# Lesson Learned

- **Data is everything -**
  - We spent too much time experimenting with the modelling - we should've explore data more. Thing we should've explore more from data side includes:
    - Social Media Data
    - Quarterly and Annual Data
    - Data Cleaning Pipeline
    - Cross Sectional Analysis on Feature Importance for assets ex. which feature effects asset<sub>i</sub> more; which feature can be excluded from asset<sub>j</sub>
- **Macroeconomics events can be significant factor, especially for week-to-week basis;**
  - We tackle this by imposing manual view on top of portfolio (ex. Increase crypto short position in weeks with inflation print).
  - But there should be quantitative and robust ways to include macroeconomic events and views into decision making framework
- **Portfolio construction -**
  - We wish we had more time to explore a portfolio, which has a high correlation to the market when its rallying and market neutral or uncorrelated portfolio when the market is selling off.
- **Don't forget to check everything -** including the checking function