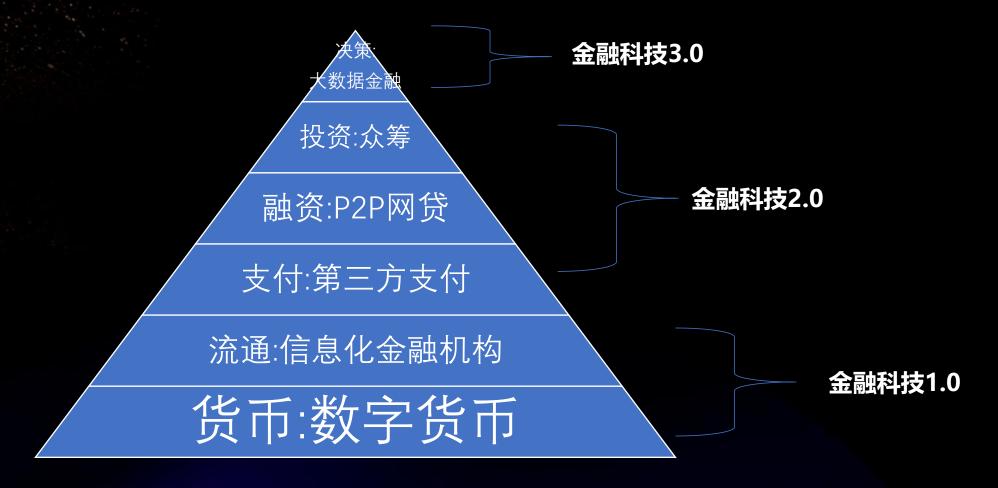
# 智能金融大数据投研平台

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# 金融科技的发展历程





## 金融科技3.0框架

计算资源 云计算

金融科技3.0 ABBC

征信 大数据



资金



记录跟踪 区块链

支付

决策

人工智能

借贷

投资



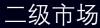
商品、服务



债权 有抵押、无抵押、自融

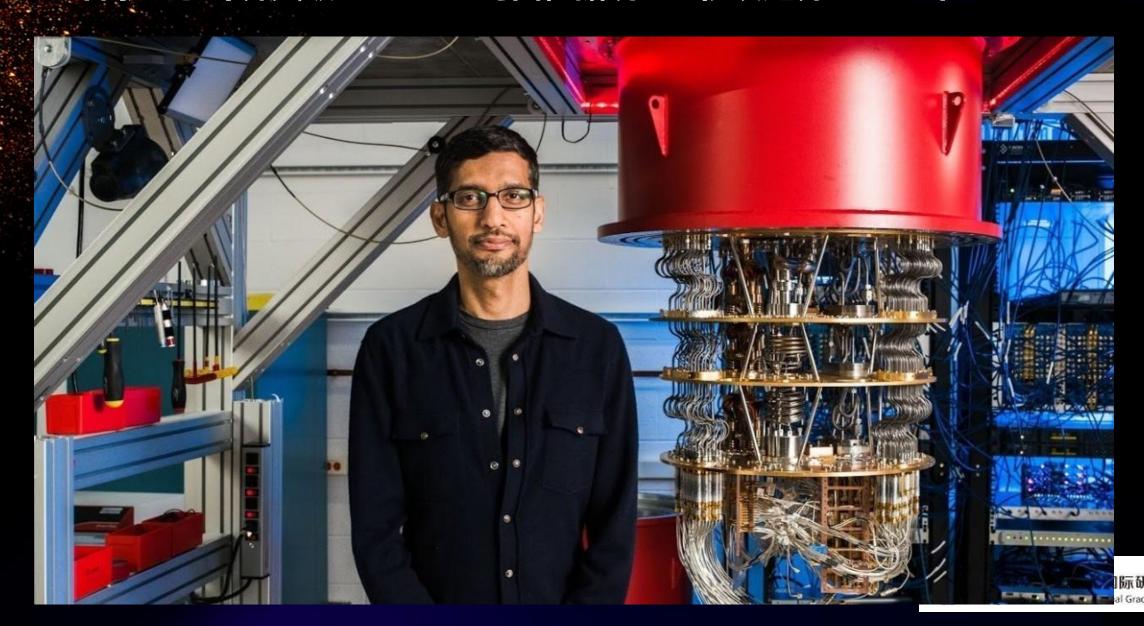


股权 一级市场





## 谷歌量子计算突破登Nature封面,据说200秒顶超算10000年





- 1 智能金融大数据投研平台框架
- 2 非结构化数据处理
- 3 机器学习算法
- 4 元知识学习算法



# 智能金融大数据投研平台框架



## 智能金融大数据投研平台框架

元知识学习算法 人类 选择 分析 模型 金融时间序列 机器学习算法

非结构化数据处理

分析模型

输入数据

特征提取

算法结构



# 非结构化数据处理



#### 新闻非结构化数据的实例

- ❖ 2013年4月23日,美联社发布推文称"两枚炸弹在白宫爆炸, 奥巴马总统被炸伤"
- ❖ 标准普尔500指数暴跌1%,一分钟内1360亿美元瞬时蒸发。





## 金融文本情感分析

**Applications:** 

Mainly in E-commerce

#### **Sentiment Analysis**

#### **Approaches**

- Lexicon-based,
- Regular Machine Learning,
- Deep Learning,
- Hybrid

#### 3 levels:

- Document level,
- Sentence level,
- Aspect level

#### **Financial Analysis**

**Current main approaches** 

- Fundamental Analysis
- Technical Analysis

Market sentiment: remarkable influences on price trends, trading volumes, volatility and potential risks Application of FSA:
Thomson
Reuters News
Analytics(TRNA)
scores



#### 各种金融文本的对比

In FSA, the sources' influences are important and the characteristics should be considered.

News cover more kinds of events than corporate disclosure.

Social media are widely analyzed despite its noise.

Some researches tend to link the sentiment of news and micro-blogs and improve the conveyance of news-contained sentiment on micro-blogs. Different financial news media have their own characteristics.

The financial articles' origin had different influences on investors.

In social media, user-profile features should be considered.

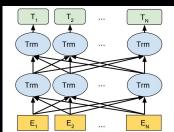


## 情感分析算法

#### Word embedding

- ■Word2Vec
- □ Global Vector (GloVe) : contain word order and global information
- □ Contextualized word embedding e.g.ELMo, GPT

Milestone: BERT (Bidirectional Encoder Representation from Transformers)



Trend: GPT-2 use a large and diverse dataset and a very deep neural network

#### CNN,RNN,LSTM,Bi-LSTM

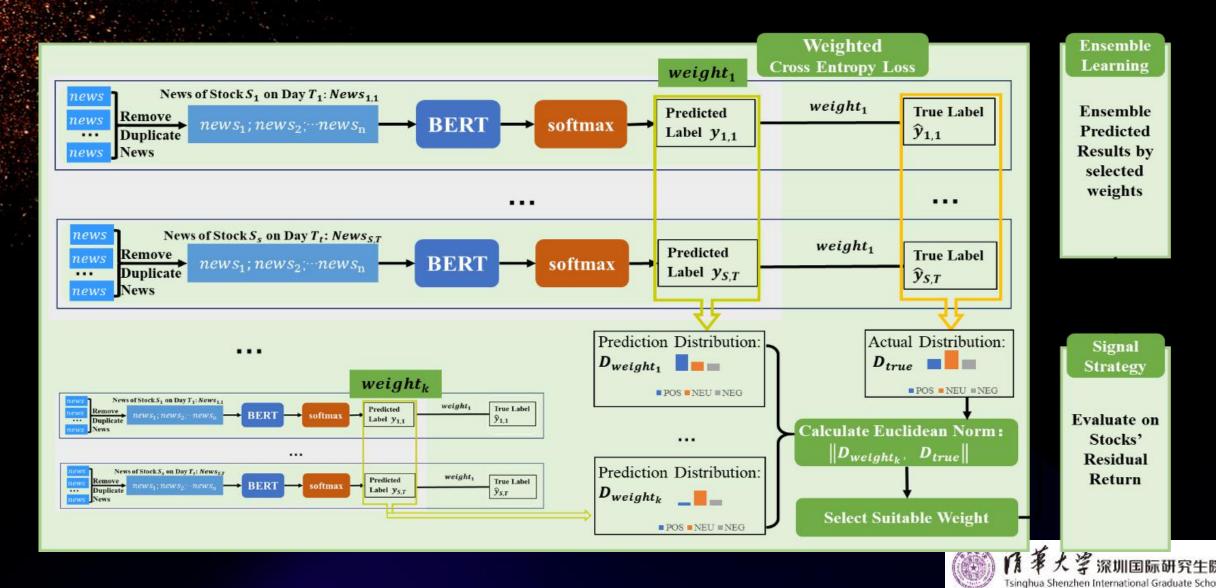
- □ Convolution Neural Network (CNN) can effectively capture local correlations of spatial or temporal structures.
- ■RNN can handle the long dependency of sequential better than CNN.
- ■Both CNN and Bi-LSTM[66] can be combined to learn the sequential correlations and extract features in a parallel way.

#### **Attention Mechanism**

- ☐ The attention mechanism allows the model to focus on the needed parts.
- ☐ Transformer is designed solely on attention mechanisms.
- ■Good at important information recognition from both sentence and aspect, position awareness and modeling the relationships between aspect terms.
- Researchers introduced the attention mechanism to explore the correlations between a financial aspect and the context.
- ☐ How to define a broadly accepted aspect in FSA needs to be discovered.



## 基于BERT的金融文本数据特异质收益分析模型



## Enhancement Learning

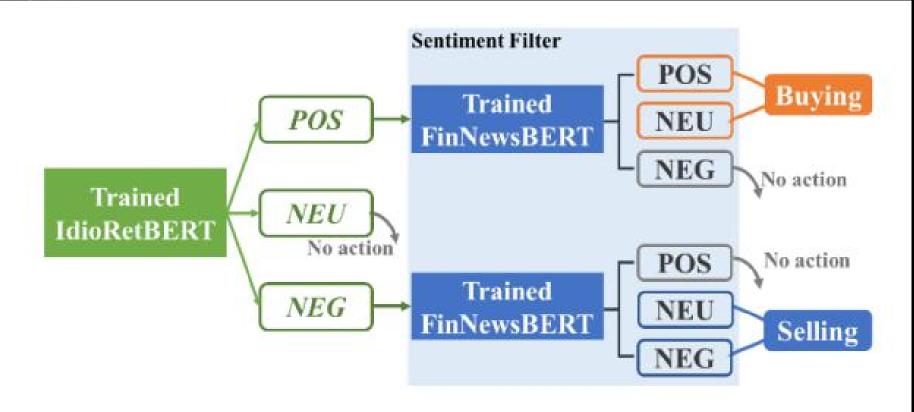
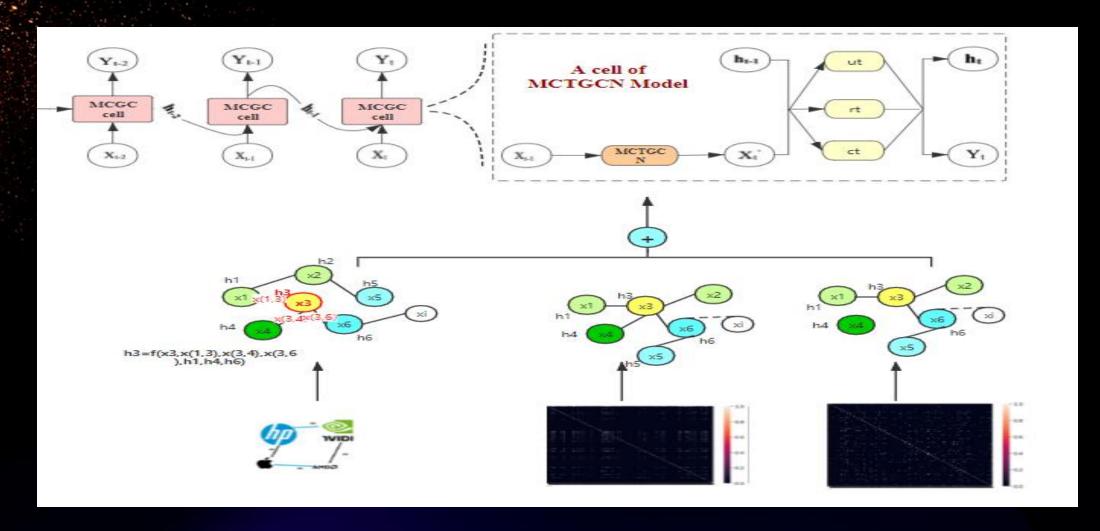


Fig. 9. The task-oriented perception-enhanced approach of EL



## 图相关金融文本数据分析模型





#### 专利大数据平台

专利是科技公司的护城河、防火墙,也是科技公司创新能力的集中体现。一直以来,学术研究焦点基本在于专利数量、专利分类以及专利引用量三个方面,经过众多学术研究表明,专利大数据是科创企业的试金石!

- 对基本面的影响: 专利数量与公司市值呈显著正相关
- 对公司股价的影响: 专利数量和专利引用量以及股票收益呈现显著正相关关系



■ 将专利研发成果细分为开发利用(短期)与探索研发(长期)两大类,开发利用类的专利可以给公司的业收入带来显著正面影响,而探索研发类的直接作用并不明显。

- 对基本面的影响: 专利引用量的增加可以帮助正向预测公司未来的现金流和收益
- 对公司股价的影响:同一公司对内部过往专利的引用 (Self-atation)比对公司外部其他专利的引用对公司 市值影响更大



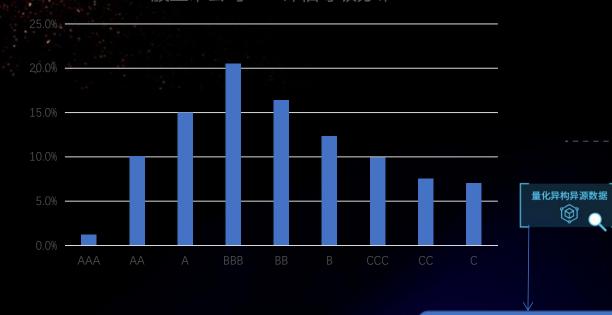


#### 信用大数据平台

#### 等级区分度明显

评估等级为AA以上的上市公司仅占上市公司的10%左右 (300至400家), 等级为AAA的公司仅占上市公司的1%左

#### A股上市公司BBD评估等级分布



引入"生态风险评估",将异构 异源的数据融合分析,降低对财

企业工商, 司法等42类数

(a)(b)(c)(d)(d)(d)(e)<l

行业上下游数据

1

务数据和专业分析师的依赖

(G) (S) (S) (E)

基于多维数据的融合分析,采用融合量化处理非结构化 与结构化数据的特征提取方法,可以对评估标的进行有 效的特征提取,实现对企业风险的多维度评估

**0 0 0 0 0** 

企业上下游数据

财务行业评估

#### 多维特征提取方法

¥

全息评级系统

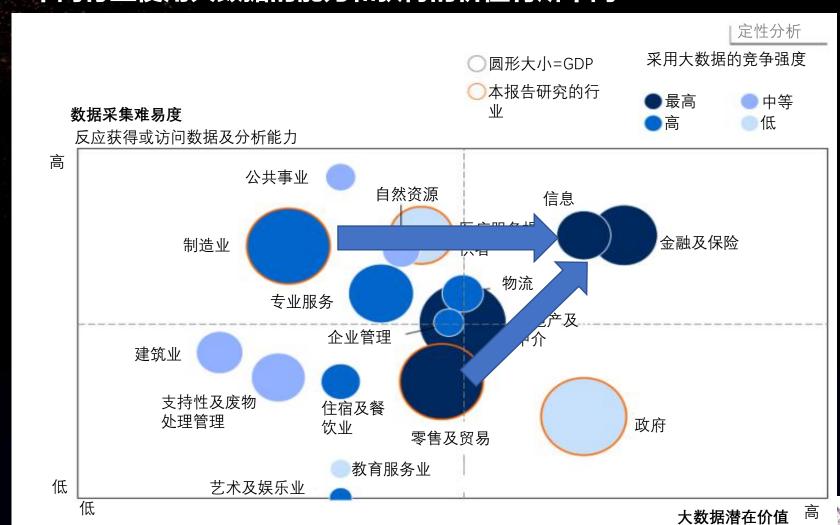
灰黑样本事件库

拥有大量灰黑样本 可以解决债券市场违 约样本不足的问题



## 大数据 - 潜在价值

#### 不同行业使用大数据的能力和获得的价值有所不同



# 机器学习算法



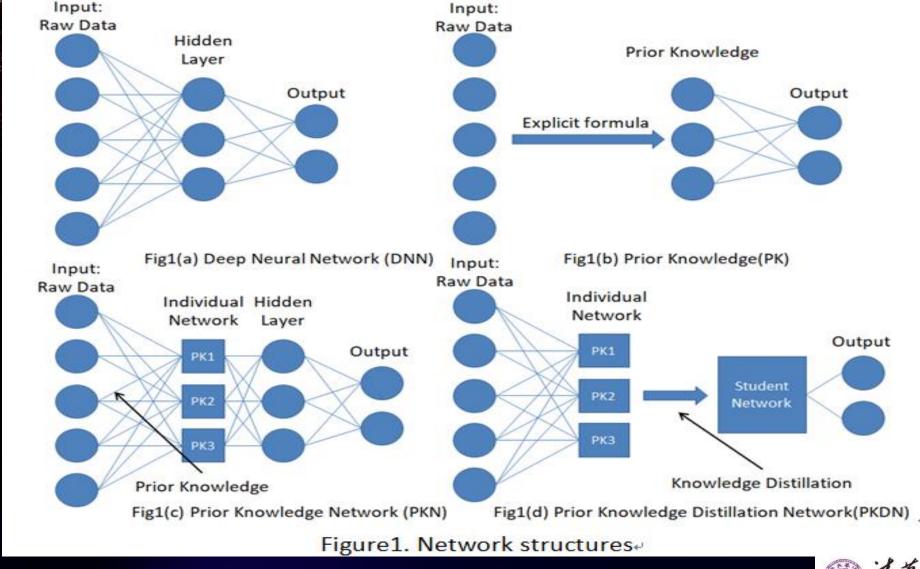
## 数据量与建模方法



#### 如何进行机器学习



#### Prior Knowledge Distillation (PKD) – High noise



#### Neural Network-based Automatic Factor Construction

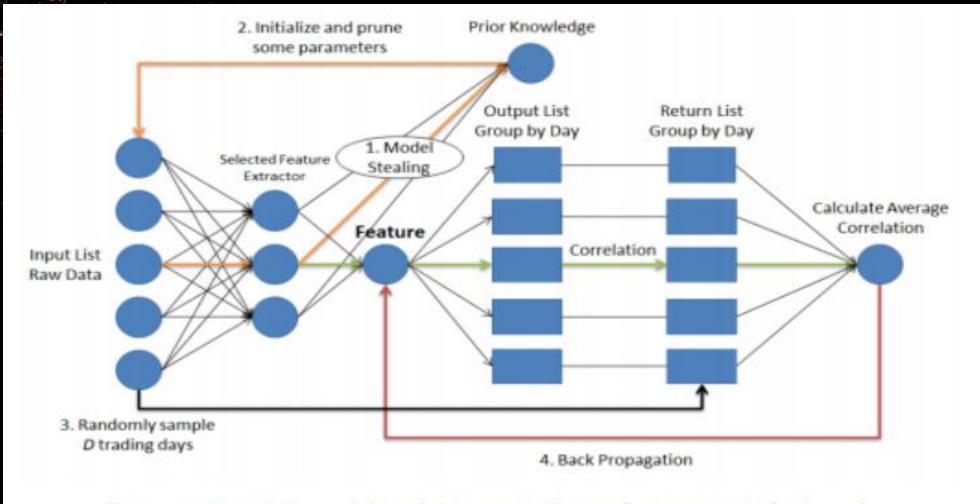
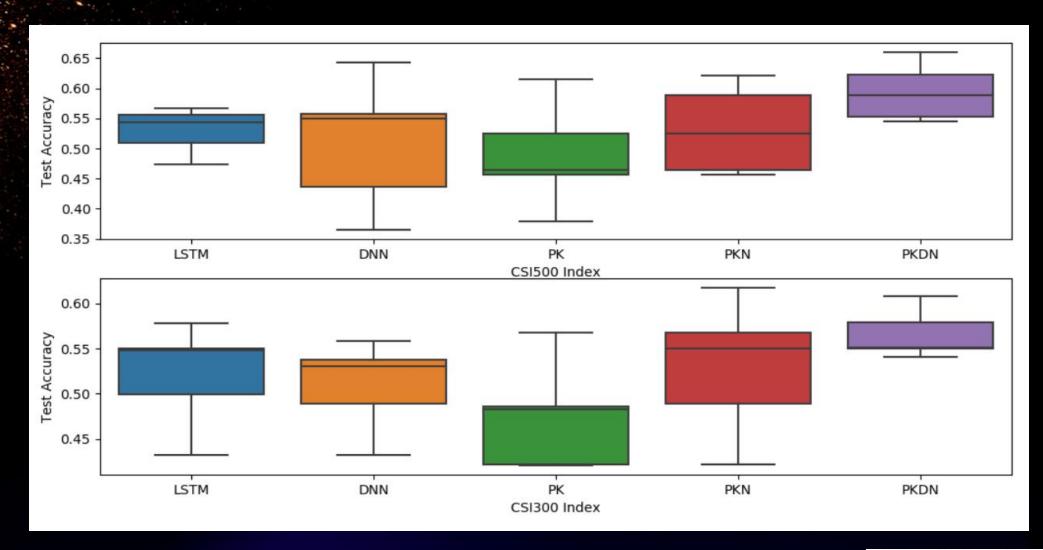


Figure 2. Neural Network-based Automatic Factor Construction's framework



#### Numerical tests for PKD





# 元知识学习算法



#### 元知识学习计算时间

Time: 100 strategies x 1000 training sets x 10000 parameter sets x
 100 seconds per simulation = 1e11 seconds

more than 3000 years

Parallel computing with 100 CPUs

more than 30 years

Apply genetic algorithm to reduce parameter sets by 10 times

more than 3 years

Use powerful GPU to speed up simulation by 10 times

more than 3 months



#### **Asymptotic Ordinal Optimization**

Partial sorting

Selecting the best

Ordinal Optimization

The underlying philosophy is to obtain good estimates through ordinal comparison while the value of an estimate is still very poor

Asymptotic Optimization

Leveraging previous simulation performance



#### **Asymptotic Meta Learning (AML)**

**Theorem 1.** Given a total number of computing time T to be allocated to k base learners whose performance is depicted by cross validation performance  $L(\theta_1, \xi)$ ,  $L(\theta_2, \xi)$ , ...,  $L(\theta_k, \xi)$  with means  $J(\theta_1)$ ,  $J(\theta_2)$ ,...,  $J(\theta_k)$ , and finite variances  $\sigma_1^2, \sigma_2^2, ..., \sigma_k^2$  and average learning time per learner  $C_1, C_2, ..., C_k$ , respectively, as  $T \to \infty$ , the Approximate Probability of Correct Selection (APCS) of Meta learning can be asymptotically maximized when

1) 
$$\frac{N_i}{N_j} = \left(\frac{\left(\frac{\sigma_i}{\delta_{b,i}}\right)}{\left(\frac{\sigma_j}{\delta_{b,j}}\right)}\right)^2, i, j \in \{1, 2, \dots k\}, i \neq j \neq b$$

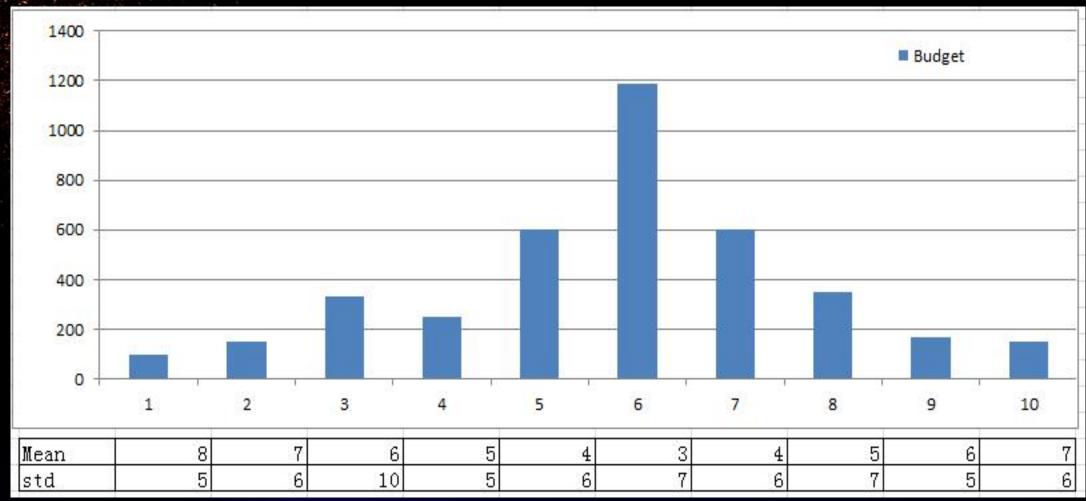
2) 
$$N_b = \sigma_b \sqrt{\sum_{i=1, i \neq b}^K \frac{C_i N_i^2}{C_b \sigma_i^2}}$$

Where  $N_i$  is the number of samples allocated to base learner  $\underline{I}_{a,b}$ ,  $\delta_{b,i} = \overline{J}_b - \overline{J}_i$ , and  $\overline{J}_b \ge \max_i \overline{J}_i$ . And

we assume  $N_b >> N_i$ .



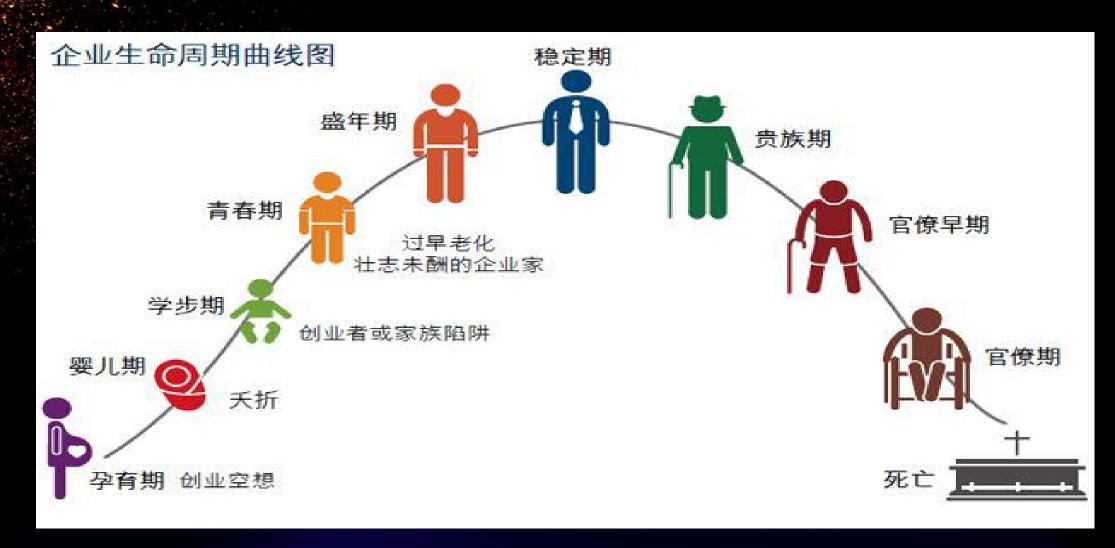
## **AML Bootstrapping**



## **AML Numerical Experiments**

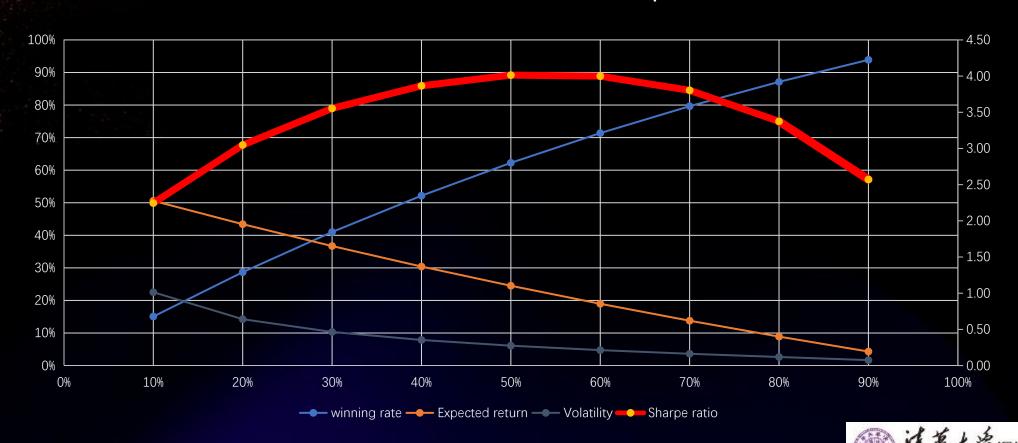
TABLE 1								
Results of numerical experiments for four Meta learning algorithms under different case								
Case 1	3.69	4.30	10.18	4.85				
Case 2	12.51	17.03	42.00	13.93				
Case 3	7.41	7.85	21.78	8.72				
Case 4	10.26	12.64	31.08	29.71				
Case 5	16.51	19.81	36.85	48.86				
Case 6	5.65	7.49	13.26	7.31				

## 生命周期算法 – 群体博弈

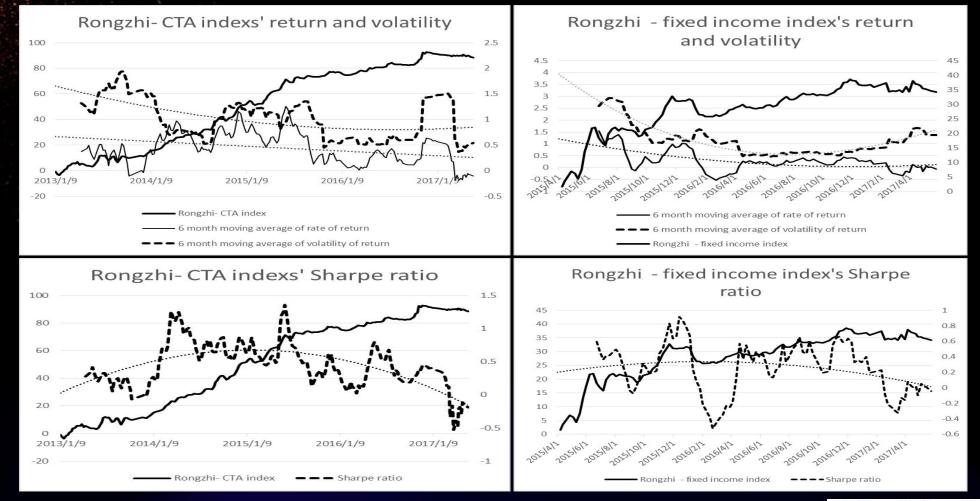


#### 生命周期模型

● 对于单个策略,在市场总资金和机构投资者信息系数保持不变的情况下,机构投资者的收益的夏普呈现Alpha周期的现象



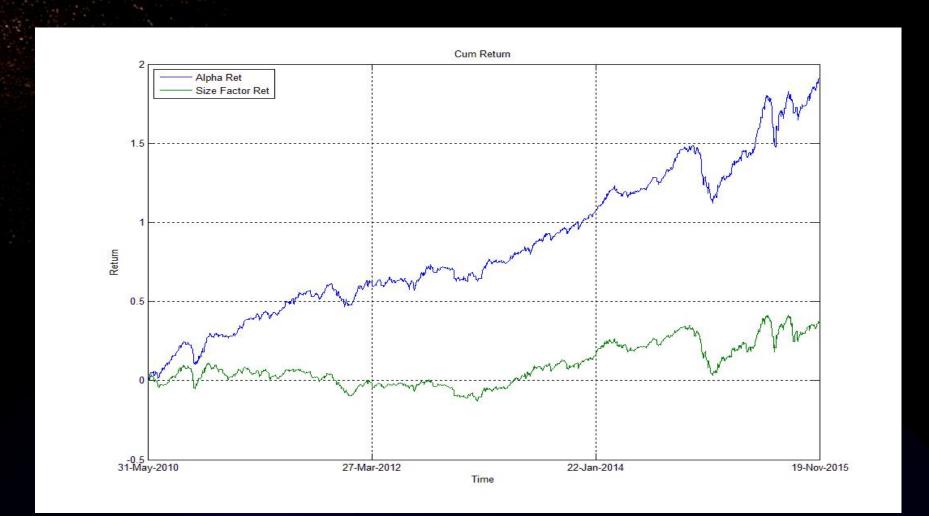
#### 实证研究





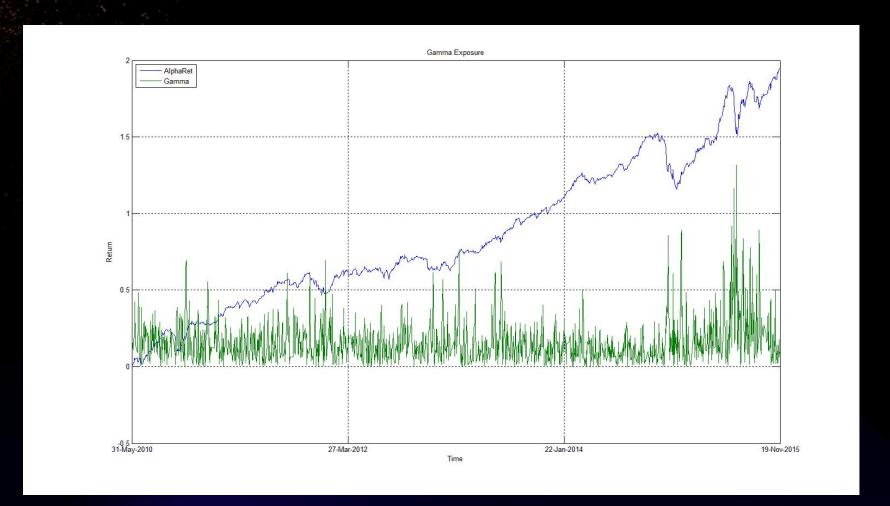
## 收益归因分析(线性)

• 超额收益有市值因子暴露



## 市场的情绪(非线性)

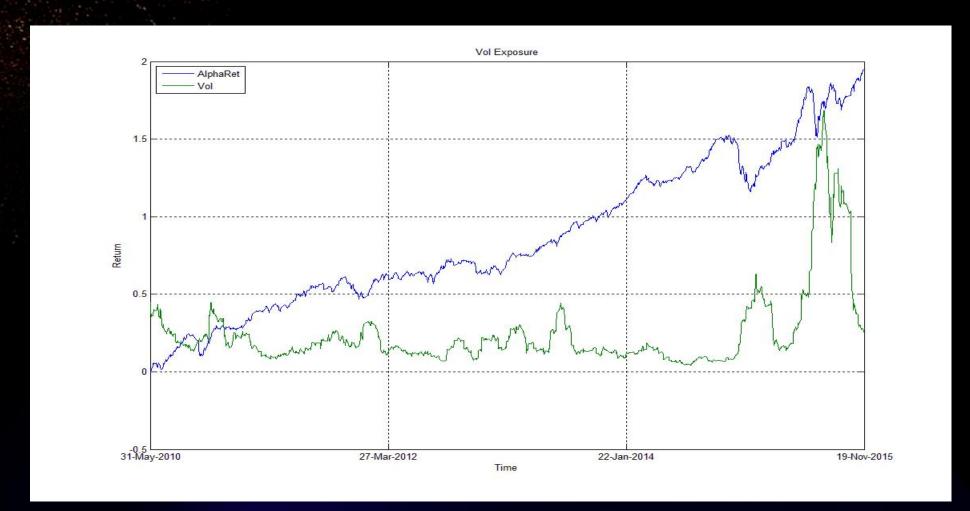
• 超额收益是空gamma的绝对值





## 波动性的预测 (非线性)

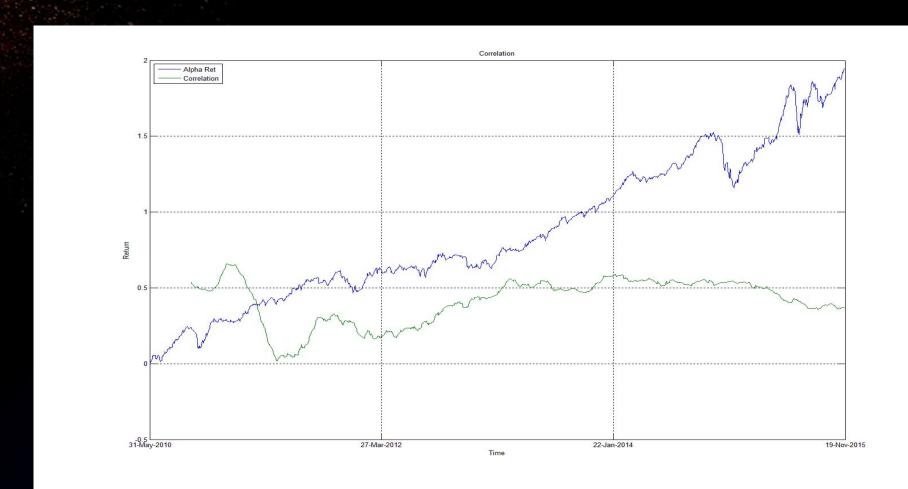
• 套利收益是空波动性





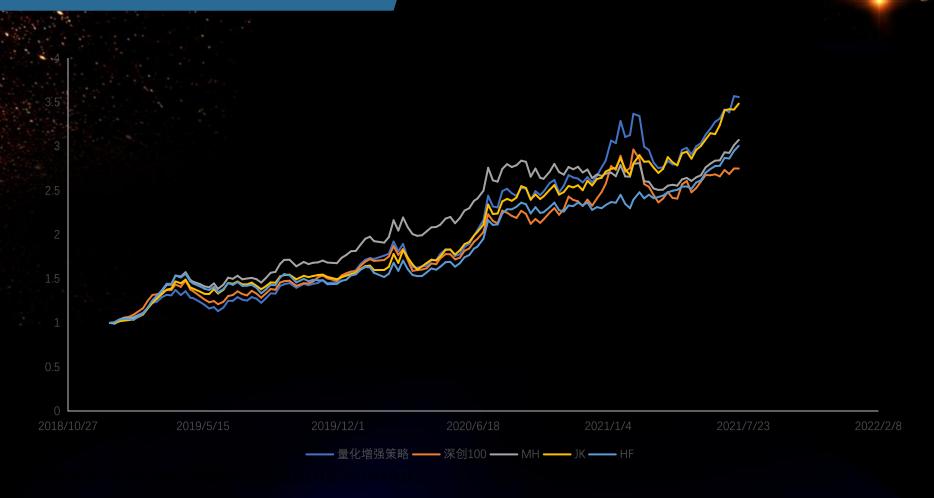
## 市场相关性的预测 (非线性)

• 持续的高相关性会导致超额收益回撤





#### 头部量化私募业绩比较



	量化增强策略	深创100	HF	JK	МН
总收益率	255.77%	174.81%	200.45%	248.25%	207.13%
波动率	23.38%	23.55%	22.90%	23.80%	23.42%





# 感谢聆听

