ALPHA DISCOVERY NEURAL NETWORK BASED ON PRIOR KNOWLEDGE

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\textbf{Abstract}

In financial automatic feature construction task, genetic programming (GP) is the state-of-the-art technique. It uses reverse polish expression to represent features and then uses genetic programming to simulate the evolution process. With the development of deep learning, there are more powerful feature extractors for option. And we think that comprehending the relationship between different feature extractors and data shall be the key. In this work, we put prior knowledge into alpha discovery neural network (ADN), combined with different kinds of feature extractors to do this task. We find that in the same type of network, simple network structure can produce more informative features than sophisticated network structure, and it costs less training time. However, complex network is good at providing more diversified features. In both experiment and real business environment, fully-connected network and recurrent network are good at extracting information from financial time series, but convolution network structure can’t effectively extract this information.

1 Introduction

Feature construction is a process that discovers missing information about the relationships among features and augments the space of features by inferring or creating new features. During this process, we can get new features from the combination of existing features [Motoda and Liu, 2002]. A more straightforward description is that we use operators, hyper-parameters and existing features to construct a new feature. Normally, feature construction is conducted by human experts. However, human can’t process sophisticated information easily, and human cost is much more than machine’s. Thus, automatic feature construction has received more and more attention [Liu and Motoda, 1998].

Sometimes both feature construction and feature selection happen in the same procedure. These methods are wrapper, filtering and embedded [Chandrashekar and Sahin, 2014]. Filtering is easy but of bad performance, it only uses some criteria to choose a feature, and sometimes it can help us to monitor the feature construction process. Wrapper performs well by directly using the model’s results to serve as object function. So we can treat an individual trained model as a new constructed feature. However, it costs a lot of computation resource and time. Embedded is a method which uses generalized factors and pruning technic to select or combine features, which serves as a middle choice between filtering and wrapper. In real practice, people prefer to use wrapper, for their good performance. Up to now, the most well-known and frequently used automatic feature construction method is Genetic Programming, which is a kind of wrapper method. It uses reverse polish expression to represent formula, and then use genetic programming to dominate its construction process. Different domains require different object function, and the input data’s data structure may be different [Krawiec, 2002]. Thus, it’s very important to do this task in a specific domain. This method has been proved to work well in many industries, such as health care [Kwakkenbos et al., 2010], object detection [Lillywhite et al., 2013], education [Romero et al., 2004], and finance [Thomas and Sycara, 1999]. However, its drawback is that the constructed formulas are very similar, and they will easily lead to collinearity.

With the development of deep learning, there is another well accepted wrapper called automatic feature construction method. People use neural network to extract feature from raw data, and then add a fully-connected layer to reshape the feature’s output. Similarly, one trained model represents one newly constructed feature. There are some relative research works, such as in pattern recognition task, Yang Zhong uses CNNs model to construct facial descriptors, this method produces features that have much more information than the past method did [Zhong et al., 2016]. K Shan conducts experiments in this task, and he uses more deep and wide convolution neural network [Shan et al., 2017]. Hidasi B uses recurrent neural network to pre-locate the feature-rich region, and successfully construct more pure features [Hidasi et al., 2016]. In text classification task, Botiss T leverages recurrent neural networks to build rule-based classifier among text data, each classifier represents a part of the text [Botiss et al., 2011]. Later, S Lai put forward a network structure which uses both recurrent and convolution neural network to extract text information. Their produced features contain more information compared with previous work [Lai et al., 2015]. As

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we can see from this development, the suitable network structure can determine the success of produced features. With the help of neural network’s strong fitting ability, we can produce highly informative features. But the drawback is that we should tailor the network structure for different industries.

In our previous work [Fang et al., 2019], we put forward a basic framework, which successfully beats the GP for tasks of automatic financial feature construction. However, financial data is very noisy. Without guidance of domain knowledge, the training of FCN can be easily trapped in local optimum. Thus, initializing ADN by existing features from prior knowledge can be a potential route to seek new features. How to effectively put prior knowledge into ADN shall be the key.

In this paper, we make two improvements. First, we conduct experiments on different kinds of feature extractors and try to understand the relationship between financial time series and these extractors. Secondly, we use prior knowledge from the capital market to initialize and diversify our networks, which makes it more powerful and suits the real-world situation. In the assessment part, we take into account the constructed features’ information coefficient, diversity, training time and back testing performance in the real situation.

## 2 Network Structure

Considering the need to make powerful features which can forecast the stock’s price in the near future, and these constructed features should have high diversity. We put forward the basic framework, Alpha Discovery Neural Network (ADN). Its structure is shown in Fig 1.

![Figure 1: Alpha discovery neural network’s structure (ADN), with its time grouped objective function, and diversity resource.](image)

### 2.1 Put prior knowledge into network

In relative value strategies of quantitative investment, we focus on the relative strength of each stock’s future return in each trading day. Thus, we let ADN propose a feature value for each stock at each trading day, and then group these results by trading day. The correlation of current feature value and this sample’s future return is our objective function. This objective function can tell the relative strength of each stock in the same trading day, and it will directly influence our investment strategy’s performance.

What’s more, model stealing [Juuti et al., 2019] and pruning [Frankle and Carbin, 2018] on input data can guarantee the existence of diversity. Model stealing means that if have already known the input x and output y, how to let our network find a suitable parameter w to fit this function as soon as possible. We use $f(x) = w^T x + b$ to embed the input data (actually, you can embed the data with several layers), and then use this embedded layer to mimic the prior knowledge. In this part, we use mean squared error to serve as object function.

$$\arg \min_w \frac{1}{n} \sum_{i=1}^{N} (y_i - f(x_i))^2$$  \hspace{1cm} (1)

After pre-train the embedded layer $f(x)$, we can get its parameter matrix $w$. Then we create a mask matrix to prune the parameter. For example, $x_{i,j}$ in parameter matrix is relatively small, which means some of the input data is useless. Then we use $m_{i,j}=0$ to permanent mask this value. If the $x_{i,j}$ is not useless, then we set $m_{i,j}=1$. This method can help us keep the diversity in the network. What’s more, it can help us focus on improving current situation, but not to heading the unknown local minimal. The pruning process is shown in formula (2):

$$f(x) = (w \cdot m)^T x + b$$  \hspace{1cm} (2)

This basic framework successfully beats the GP on automatic financial feature construction task. However, financial data is very noisy. Without guidance of prior knowledge, the training of FCN can be easily trapped in local optimum. Thus, initializing ADN by existing features from prior knowledge can be a potential route to seek new features. How to effectively put prior knowledge into ADN shall be the key. Thus, in this paper, we use prior knowledge to serve the source of diversity. Meanwhile, we conduct experiments on different feature extractors, for having better understanding of the financial time series. A lot of experiments show that different feature extractors have its own strong comings and shortcomings on this task, these performances varies on information coefficient, diversity, training time, strategy return, etc.

### 2.2 Different feature extractors

There are two motivations to use different feature extractors. At first, different feature extractors require different input data’s data structure. After doing literature review and consulting professional experts in the market, we find that there are many different ways to organize the input data. But none of them can prove that their structure is the best. Thus, it’s meaningful to do experiments on all of these structures. These networks’ input data structures are shown in Fig 1.

The second motivation is that different extractors have their own strong comings and short comings. Some of them aim at extracting temporal information but the others aims at spatial information. Some of them designed for a long term series, but some of them are designed for quick training. The following numerical experiments can help us have better understanding for their characteristics.
3 Experiments

3.1 Experiment setting

We use daily trading data in A-share stock market, including daily open price, high price, low price, close price and trading volume in the past 30 trading days. We standardize the raw data by using its mean and standard deviation. Both the mean and standard deviation are calculated from training set. We try to use these inputs to predict the stock return in the next 5 trading days.

During the model training process, we calculate the average value of spearman correlation in 20 randomly selected trading days. For each experiment, 250 trading days serve as training set, the following 30 trading days serve as validation set, and the following 90 trading days serve as testing set. We use same setting for the GP algorithm. In order to make a fair compare, we need to make sure our GP is correct and powerful. This algorithm’s logic refers to relative work [8,24]. Secondly, the input data should be the same. The prior knowledge used in this experiment is 50 common quantitative hedge trading indicators based on only price and trading volume information.

In this paper, we analyze the construed features’ performance from different perspectives. Normally, institutional investors uses information coefficient (IC) to measure how much information carried by a feature.

\[
IC(x, y) = \frac{\text{cov}(\text{rank}(x - \bar{x}), \text{rank}(y - \bar{y}))}{\text{var}(\text{rank}(x - \bar{x}) \ast \text{var}(\text{rank}(y - \bar{y})))}
\]  

In formula (3), x refers to feature value, y refers to sample’s return in the next 5 trading days, rank is an operator which get the rank of a given series, cov is an operator to calculate covariance, and var is an operator to calculate variance. As for diversity, we uses cross entropy to measure the distance between different features’ distribution in the same trading day. Cross entropy is not symmetric, but the experiment shows it doesn’t have much effect. Then we cluster this distance matrix by using k-means. The average distance between each cluster center refers to the diversity of this algorithms’ diversity in this trading day.

\[
\text{Distance}(f_1, f_2) = \sum \text{softmax}(f_1) \log \frac{1}{\text{softmax}(f_2)}
\]

In formula (4), \(f_1\) and \(f_2\) refers to different features’ distribution in the same trading day. The softmax function can help us get rid of the effect from scale. Meanwhile, we will not loss its rank information. After we get the distance matrix which can show the relative distance between two objects, then we cluster this distance matrix by using k-means. The average distance between each cluster center refers to the diversity of this algorithm in this trading day. Besides IC and Diversity, we also use the constructed features to form a multi-factor strategy. After back testing this strategy, we can get its absolute return, max-drawdown and sharp-ratio. Basically, all these indicators are really important to assess a feature’s performance.

3.2 Beat the state-of-the-art technic

In our previous work [2019], we successfully used ADN to beat the genetic programming algorithm, without the help of prior knowledge. We put forward three schemes to help illustrate ADN’s contribution. The results are summarized in table 1. Only GP means only using genetic programming, Only Mine means only use ADN, GP & Mine means uses GP’s value to initialize ADN.

| Object | Information Coefficient | Diversity |
|--------|-------------------------|-----------|
| Only GP | 0.094 | 17.2T |
| GP & Mine | **0.122** | **25.44** |
| Only Mine | 0.107 | 21.65 |

As shown in Table 1, Only Mine is better than Only GP. Besides, GP & Mine is the best, which means our method can improve the performance of GP. Because this is not the contribution of this paper, we only restate this conclusion without any further discussion. The main contribution of this paper is to show the characteristics of different feature extractors. And in previous work, we only show that ADN can get features which have higher IC and Diversity. In this work, we conduct experiments to show its usage and contributions in the real situation.

3.3 Comparing different feature extractors

In the following experiments, we mainly compare different neural networks’ out-of-sample performance. All the experiments are conducted in the same setting mentioned in section 3.1, and the results are summarized after generating 50 features. For the hardware equipment, we use 20g GPU (NVIDIA 1080Ti), 786g CPU (Intel Xeon E5-2680 v2, 10
cores). GP mainly relies on CPU, but deep learning algorithms mainly rely on GPU. In our experiments, we almost make full use of these resources. At first, we plot the average information coefficient in each trading day.

![Figure 3: Average information coefficient in each trading day.](image)

As we can see from Fig 3, although the information coefficient changes greatly, almost all these curves show the same tendency. Because sometimes these technical factors work well, sometimes almost all technical factors will perform badly on the market. Thus, we think this framework will be beneficial to a portfolio manager’s technical factor pool, and improve their current situation. All the details are summarized in Table 2.

| Type       | Network | IC    | Diversity | Time     |
|------------|---------|-------|-----------|----------|
| Baseline   | GP      | 0.072 | 17.532    | 0.215 hours |
| Vanilla    | FCN     | 0.124 | 22.151    | 0.785 hours |
| Spatial    | Le-net  | 0.123 | 20.194    | 1.365 hours |
|            | Resnet-50 | 0.108 | 21.403    | 3.450 hours |
| Temporal   | LSTM    | 0.170 | 24.469    | 1.300 hours |
|            | Transformer | 0.111 | 25.257    | 4.151 hours |

Basically, all neural networks can produce more diversified features than using GP. But temporal extractors are especially better at producing diversified features, such as LSTM [Hochreiter and Schmidhuber, 1997] and Transformer [Vaswani et al., 2017]. We think these extractors are good at filtering input data. A reasonable method to constrain input information may be helpful to enlarge the diversity. As for TCN [Lea et al., 2017], the author who put forward this network structure proves its ability to capture the temporal rules buried in data. However, there is a huge difference. TCN relies on convolution neural network, but LSTM and Transformer still contains recurrent neural network (Normally, transformer uses recurrent neural network to embed the input data). The existence of recurrent neural network structure may contribute to the difference of diversity. For Le-net [LeCun et al., 1998] and Resnet [He et al., 2016], they don’t provide us with more informative features. We suspect that the convolution network structure is not suitable to extract information from financial time series.

Here, we also show how much time we need to train 50 neural networks. However, if we have got 50 trained networks, the time to restore them and get its feature value will be much faster than traditional features. Because most traditional features are made of complicated explicit formulas, which are not suitable for matrix computing. If we use neural network to represent features, all the steps are matrix computing. Besides, it fully support GPU acceleration. We also plot the average IC in different trading days.

To sum up, we find that all neural networks mentioned above can produced more informative and diversified features than GP. For the same type of networks, the sample network performs relatively better than the sophisticated networks.

### 3.4 Real-world use case

In the real world, we usually combine human experts’ features and constructed feature to maximize the performance of the quantitative investment strategy. In training set, we label the sample whose return ranked in the top 30% in each trading day as 1, and label the sample whose return ranked in the last 30% in each trading day as 0. We abandon the rest of samples in training set. After training these features with XGBoost [Chen et al., 2015], use binary logistics mode, we will get prediction result, whose value reflects the odds that this stock has outstanding performance in the following 5 trading days.

More specifically, we regard the 50 features constructed by human experts as **PK 50**, the features constructed by GP as **GP 50**, the features constructed by both GP and PK as **GP-PK 50**. In separate experiments, we use XGBoost to pre-train both PK 50 and GP 50 in training set, and then using the weight score from XGBoost to choose 50 most important features as **Combined 50**. The back testing results are summarized in Table 3.

| Type       | Target Group | Strategy Group | Return  | Max Drawdown | Sharpe Ratio |
|------------|--------------|----------------|---------|--------------|--------------|
| Baseline   | ZZ500 Stock Index | 19.60% | 13.50% | 1.982 |
|            | HS300 Stock Index | 18.60% | 20.30% | 1.606 |
|            | PK PK 50 | 24.70% | 18.90% | 2.314 |
|            | GP GP 50 | 17.60% | 25.30% | 1.435 |
|            | GP-PK 50 | 25.40% | 14.80% | 2.672 |
| Vanilla    | FCN New 50 | 20.60% | 15.80% | 2.189 |
|            | Combined 50 | 29.60% | 15.70% | 3.167 |
| Spatial    | Le-net New 50 | 20.60% | 15.80% | 2.189 |
|            | Combined 50 | 29.60% | 15.70% | 3.167 |
|            | Resnet-50 New 50 | 19.90% | 15.40% | 1.962 |
|            | Combined 50 | 29.30% | 17.20% | 2.787 |
| Temporal   | LSTM New 50 | 19.50% | 15.00% | 2.205 |
|            | Combined 50 | 29.90% | 15.00% | 3.289 |
|            | TCN New 50 | 22.40% | 14.70% | 2.440 |
|            | Combined 50 | 26.90% | 16.80% | 2.729 |
|            | Transformer New 50 | 21.10% | 15.90% | 2.203 |
|            | Combined 50 | 27.20% | 15.10% | 2.806 |
As shown in table 3, HS300 and ZZ500 is important stock index in A-share market. Comparing with these indexes can show our strategy’s performance regardless of macro environment. Strategy return means how much we can win by using this strategy. Max-drawdown means if we keep on using this strategy during this period of time, how much we loss in the worst case. Sharp-ratio means how much we can win after considering the risk. This indicator can show the strategy’s performance, both considering revenue and risk.

If we only use the new 50, although they all have higher IC than the PK 50, this strategy doesn’t get higher strategy return. After calculating the diversity of features constructed by human experts, we find it’s remarkably higher than the automatic constructed features. Low diversity will cause collinearity and reduce the contribution of constructed features to the strategy. Thus, it’s reasonable to choose the features among the new and existing human experts’ features, and this approach is more reasonable and more suitable for practical application.

In all cases, our combine 50 is better than PK 50 and GP-PK 50, which means, with a reasonable feature selection process, ADN can construct more useful features than GP, also it have brought benefits for the existed feature pool, PK. From the perspective of Sharpe-ratio, all neural networks perform much better than the baseline. What’s more, similar to the conclusion in section 3.3, in the same type of model, the simple networks perform better than the sophisticated networks, and temporal information is more valuable than spatial information.

We also plot exceed return curve over HS300 index in Fig. 4. We pick PK50, GP-PK50, and different feature extractors’ combine 50.

![Figure 4: Different feature extractors’ exceed return in testing set (hedge on HS300 Index)](image)

As we can see from Fig 4, all these curves are similar, due to the fact that they all shared some factors from PK50. GP’s curve is always in the lowest position, which means GP provide us with fewest effective trading signals. However, all these schemes have positive exceed return, which means all these schemes and all these features are useful, and they successfully beat the market. Among the schemes powered by ADN, FCN and LSTM perform best. During this period of time, they have beaten the market more than 10 percent. We think it’s a pleasant performance, because all the features are only constructed from price and stock’s volume. They don’t contain any fundamental data or even sentiment data. What’s more, we will get a lot of extra information during feature construction process. This information is helpful to feature selection process. That’s the main reason why some wrapper methods will do feature selection and construction at the same time. For further research, we want to improve the current structure, which conduct the feature construction and feature selection process at the same time. In this work, we directly use this reasonable feature selection method, because we only focus on feature construction task.

### 3.5 Comprehend experiment result

Normally, sophisticated networks can extract more information from raw data than simple networks. However, in this case, simple networks extract more information than sophisticated networks. There are potential reasons. Firstly, in order to implement this paper’s task, we have to make small adjustments on the existing networks. These adjustments are really small, but they may put the network in a very poor position. Secondly, the raw data is financial time series, all the sophisticated networks contains too much tailored design for the other tasks. Thus, they don’t achieve success in this task.

In order to test the first suspect, we keep these adjustments and test their performance in their previous tasks. Renet-50 is designed for picture recognition problem, so we run this experiment on MINIST and CIFAR-10 [He et al., 2016]. TCN and Transformer are designed for time series problem. Thus we conduct experiments on PM2.5 and ENERGY, and there are some benchmarks for comparing [Qin et al., 2017].

| Type | Network | MNIST | CIFAR-10 |
|------|---------|-------|----------|
| Spatial | Le-net | 99.75±0.05% | 75.11±0.21% |
|       | Resnet-50 | 99.82±0.04% | 85.75±0.25% |
| Type | Network | PM2.5 | ENERGY |
|------|---------|-------|---------|
| Temporal | DUAL | 25.53±0.08 | 40.30±0.11 |
|       | RETAIN | 61.22±0.49 | 54.77±0.11 |
|       | cLSTM | 83.59±0.05 | 65.42±0.32 |
|       | MV-LSTM | 24.79±0.09 | 39.81±0.03 |
|       | TCN | 20.95±0.04 | 58.70±0.38 |
|       | Transformer | 21.52±0.23 | 61.37±0.65 |

From table 4, we find that all these networks still perform well in their previous task. That means these small adjustments don’t ruin their performance in their previous task. Thus, we think the second suspect will be more reasonable. The second suspect is that, all the other complicated networks are not designed for this task, and complicated network structure contains too much tailored structure which is not good for this task.
But, what structure is exactly suitable for this paper’s task? In section 3.3, we find that LSTM extracts more information than FCN. We suspect that only the recurrent structure and fully connected structure are helpful to extract information from financial time series. All the other complicated networks are not designed for this task, thus, they can provide extra diversity, but they can’t extract too much information. In order to verify this idea, we construct 150 features by using FCN, Le-net and LSTM. And then we cluster their diversity by using k-means, this method has been mentioned in section 3.1. But in order to visualize this distance matrix, it’s better to transform this matrix in to a 2-D graph. We initialize one of the cluster center as (0,0), and then determine the other two cluster centers according to their relative distance and a given direction. (This direction will only influence the outlook of this graph, but it will not influence the shared space between different clusters.) For the other samples belong to the same cluster, we determine their location according to their relative distance with cluster center and a randomly generated direction. Every time we only make three clusters, this setting can make it easier for us to find the correlation between each feature extractors. All these 150 features are visualized in Fig 5.

As shown in Fig 5 (a), the features constructed by LSTM have most sparse distribution. It means the network structure which focuses on temporal information is really good at extracting information from financial time series. However, there are large space shared by FCN and Le-net. We can regard Le-net’s information as a subset of FCN. Combined with convolution neural network’s poor performance in section 3.2 and 3.3, we think the convolution structure doesn’t make much contribution to extracting information from financial time series. Meanwhile, FCN almost has no space shared with LSTM. Fig 5(c) is an extra experiment, which used to support this conclusion. Thus we think fully-connected structure and recurrent structure are helpful to extract information from financial time series.

Comparing Fig 5(a) and Fig 5(b), we find that the features constructed by complicated networks have larger radius than the features constructed by simple networks. Comparing g Fig 5(a) and 5(d) can also support this conclusion. What’s more, this conclusion also commits to our previous finding in section 3.3, that complicated networks are good at adding diversity.

To sum up, we want to construct features from financial time series, which can forecast the stock’s performance in the near future. But different kinds of feature extractors perform differently. Fully-connected structure and recurrent structure is suitable for this task. And let’s look back at Fig 2, different feature extractors require different input data’s structure. Now we can make some conclusions. Firstly, it’s not reasonable to shape the financial time series as a picture. Financial time series has much fewer points than a picture’s pixel, which means it’s not a high-dimension data, compared with picture. But convolution and pooling structure is designed for extract information from high dimension data, that’s the reason why this network and input data’s structure is not as competitive as other structure in this task. Secondly, fully-connected structure can both deal with high dimension and low dimension data. We guess this is the main reason why convolution structure’s contribution in Fig 5 (a) is only the subset of fully-connected structure. Thirdly, recurrent structure’s performance is outstanding. We think the time decay principle in this structure makes it more suitable to extract information from financial time series. At last, although different structure performs differently on this task, all of them have contributed to the diversity of constructed features, and their performance is better than genetic programming, both in numerical experiment and real-world case. That’s also highly valuable.

4 Conclusion

In this paper, we use alpha discovery neural network, equipped with different SOTA networks and different prior knowledge from human experts, to do financial automatic feature construction task. We find that both in numerical experiment and in real-world use case, all the networks can produce more informative and diversified features than genetic programming, which is the state-of-the-art technic in this task [8,24]. More specifically, fully-connected and recurrent structure is good at extracting information from financial time series, but convolution structure can’t effectively extract this information. Besides, in the same type of network, simple network structure can produce more informative features than sophisticated network structure, and it costs less training time. However, complex network is good at providing more diversified features.

For further research, we think this framework may also be suitable for company’s fundamental data and sentiment data. We will conduct experiments on this data and try to enrich the traditional fundamental factors pool.
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