DenseNet Feature Embeddings for Thoracic Disease Diagnosis

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Introduction

Client X-ray scans are the most frequent type of radiology exam worldwide, and are commonly used to diagnose pneumonia, lung cancer, and dozens of other thoracic diseases. However, proper diagnosis is challenging, as a single scan can reveal multiple illnesses, and radiologists often disagree in their diagnoses. In recent years, deep convolutional neural networks have been shown to approach or even exceed human doctors at this diagnosis task. In this work, we build on the DenseNet-based models developed in several recent papers (CITATIONS). To understand the behavior of these models, we investigate feature embedding vectors output by DenseNet and find that they exhibit clustering properties. By leveraging these embeddings with different classification algorithms, we produce new state-of-the-art results for thoracic disease classification.

Dataset

**Time series data of stock price of INTC**

<table>
<thead>
<tr>
<th>Data resource:</th>
<th><a href="https://www.alphavantage.co/stock-market/price/">https://www.alphavantage.co/stock-market/price/</a></th>
</tr>
</thead>
<tbody>
<tr>
<td>Data classes:</td>
<td>T/L</td>
</tr>
<tr>
<td>Data set size:</td>
<td>Train set: 2 years, Test set: 3 months (1)</td>
</tr>
<tr>
<td>Input:</td>
<td>Previous 5 days’ prices and log returns, Open/Close price, High/Low price, and trading volume. These variables provide basic information about the company. The second set is the technical indicators that demonstrate various characteristics of the stock behavior. The third set is the intc trading database.</td>
</tr>
<tr>
<td>Model:</td>
<td>S&amp;P 500 (SPX), CBOE Volatility Index (VIX), and S&amp;P lumber feature vector (&quot;Lumber&quot;)</td>
</tr>
</tbody>
</table>
| Output: | Daily Trading Data of INT:
- Previous 5 days’ prices and log returns
- Open/Close price, High/Low price, and trading volume |
| Decision: | Technical Indicators of INT (computed based on the trading data):
- Rolling Average/Standard Deviation with 5 and 10 days window
- Bollinger Bands: two standard deviations from a moving average
- Average True Range: a measure to volatility of price
- 1-month Momentum: the difference between current price and the price 1 month ago |

Models

**DenseNet Architecture**

- **Block Structure:**
  - Input:
  - Dense Block 1
  - Dense Block 2
  - Dense Block 3
  - Predictions

**Parameters For DenseNet:**
- Optimizer: Adam
- Learning Rate: 0.001
- Hidden layers: 100
- Dropout: 0.5
- Training Step: 5000

Embedding Analysis

Experiments

<table>
<thead>
<tr>
<th>Period</th>
<th>CheXNet</th>
<th>DenseNet [1]</th>
<th>One-to-Many</th>
<th>Random Forest</th>
<th>k-Nearest Neighbors</th>
<th>Embedding</th>
</tr>
</thead>
<tbody>
<tr>
<td>February</td>
<td>0.8090</td>
<td>0.8000</td>
<td>0.7998</td>
<td>0.7502</td>
<td>0.7204</td>
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</tr>
<tr>
<td>March</td>
<td>0.8240</td>
<td>0.8147</td>
<td>0.8090</td>
<td>0.6945</td>
<td>0.9118</td>
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</tr>
<tr>
<td>April</td>
<td>0.8080</td>
<td>0.8080</td>
<td>0.8080</td>
<td>0.8080</td>
<td>0.8080</td>
<td></td>
</tr>
<tr>
<td>May</td>
<td>0.8260</td>
<td>0.8260</td>
<td>0.8260</td>
<td>0.8260</td>
<td>0.8260</td>
<td></td>
</tr>
<tr>
<td>June</td>
<td>0.8460</td>
<td>0.8460</td>
<td>0.8460</td>
<td>0.8460</td>
<td>0.8460</td>
<td></td>
</tr>
</tbody>
</table>

Conclusion

- Deeper DenseNets, along with careful tuning, can improve the accuracy of diagnosis on chest-X-rays.
- The performance of LSTM is more robust than UWR: LSTM has smaller MSE than UWR for both Train and Test Set, and it has less deviation in the prediction error plot.
- The strategy based on LSTM yields higher returns and Sharpe Ratio than UWR-based strategy and simple Buy and Hold Strategy.
- However, the prediction by these models become inaccurate when the price changes dramatically.

Outlook

- Tuning hyper parameters and adding regularization term would improve the performance of LSTM.
- Trading strategy with reinforcement learning could generate more stable and higher returns.

References

1. [Andres et al.: High-Frequency Trading Strategy Based on Deep Neural Networks(2016)]
2. [Hands-On Machine Learning with Scikit-Learn and TensorFlow]
3. [A deep learning framework for financial time series using stacked autoencoders and long short term memory]
4. [Understanding LSTM Networks, Colah’s blog. http://colah.github.io/posts/2015-08-Understanding-LSTMs/]

*All of the variables are scaled between 0 and 1 before we feed them into the model.*