Rankings of financial analysts as means to profits

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Motivation

Rankings of financial analysts:

- Long debate on whether analysts create value to investors;
- Rankings could be useful because they signal the top analysts.
- Predicting the rankings of analysts can lead to successful trading strategy based upon that information

Goal

- Accurately predict the ranking of financial analysts
- Develop a trading strategy based on predicted rankings

Label Ranking

- Instance: $\mathcal{X} \subseteq \{\mathcal{V}_1, \ldots, \mathcal{V}_m\}$
- Labels: $\mathcal{L} = \{\lambda_1, \ldots, \lambda_k\}$
- Output: $\mathcal{Y} = \Pi_{\mathcal{L}}$
- Training set: $\mathcal{T} = \{x_i, y_i\}_{i \in \{1,\ldots,n\}} \subseteq \mathcal{X} \times \mathcal{Y}$

Learn a mapping $h : \mathcal{X} \to \mathcal{Y}$ such that a loss function ℓ is minimized:

$$\ell = \frac{\sum_{i=1}^{n} \rho(y_i, \hat{y}_i)}{n} \tag{1}$$

with ρ being a Spearman correlation coefficient:

$$\rho(y, \hat{y}) = 1 - \frac{6 \sum_{j=1}^{k} (y_j - \hat{y}_j)^2}{k^3 - k} \tag{2}$$

where y and $\hat{y}$ are, respectively, the target and predicted rankings for a given instance.

Naive Bayes for LR

Adapting naive Bayes classification algorithm requires defining posterior and conditional label ranking probabilities. Define $\mathcal{S}$ as a similarity matrix between the target rankings in a training set, i.e. $\mathcal{S}_{n \times n} = \rho(y_i, y_j)$. The prior probability of a label ranking is given by:

$$P_{LR}(y) = \frac{\sum_{i=1}^{n} \rho(y, y_i)}{n} \tag{3}$$

The conditional label ranking probability given its rankings is:

$$P_{LR}(v_{a,i}|y) = \frac{\sum_{i:x_{i,a}=v_{a,i}} \rho(y, y_i)}{|\{i : x_{i,a} = v_{a,i}\}|}$$

Extensions:

- Case of continuous independent variables:

$$P_{LR}(x_i|y) = \frac{1}{\sqrt{2\pi}\sigma_y} e^{\frac{(x_i-\mu_y)^2}{2\sigma_y^2}}$$

where μ_y and σ_y^2 are weighted mean and weighted variance and defined as follows:

$$\mu_y = \frac{\sum_{i=1}^{n} \rho(y, y_i) x_i}{\sum_{i=1}^{n} \rho(y, y_i)}$$

$$\sigma_y^2 = \frac{\sum_{i=1}^{n} \rho(y, y_i)(x_i - \mu_y)^2}{\sum_{i=1}^{n} \rho(y, y_i)}$$

- Timing in rankings:

$$P_{LR}(y) = \mathbf{w} \frac{\sum_{i=1}^{n} \rho(y, y_i)}{n}$$

where $\mathbf{w}$ is the vector of weights calculated as:

$$\mathbf{w} = \alpha^{\frac{T_{1,\ldots,t}}{T} - 1} \text{ where } t \leqq T$$

Trading strategy

The views are made of: Q—the expected stock return; Ω—the confidence of Q. The trading strategy is applied as follows:

1. For each stock s, at the beginning of quarter q, we predict the rankings of all analysts that we expect to be at the end of the quarter q;
2. Based on these predicted rankings and analysts' price targets, we define $Q_{q,s}$ and $\Omega_{q,s}$;
3. Using market information available at the last day of quarter $q-1$, we obtain the market inputs;

Results

Strategy	Return (in %)	Std. dev (in %)	SR	Num. stock	Turnover
Market	-3.032	16.654	-0.182	499	0.053
true	1.785	15.312	0.117	240	0.272
recent	0.634	15.444	0.041	240	0.251
all-time	0.587	15.325	0.038	240	0.238
`last`	0.513	15.478	0.033	240	0.262
`diff`	0.779	15.507	0.050	240	0.269
`random`	0.671	15.474	0.043	240	0.258
`roll.sd`	0.634	15.464	0.041	240	0.264

Conclusion

In this paper we developed an algorithm that is able to predict the rankings based on state variables that characterize the information environment of the analysts. Further, we designed and operationalized a trading strategy based on the Black-Litterman model with rankings as inputs. We obtained positive successful results from trading that out-performs both the market and the baseline ranking prediction.

Independent variables

State variables:

- Analysts' dispersion;
- Analysts' information asymmetry;
- Analysts' uncertainty;
- Stock return volatility;
- Book-to-market ratio;
- Debt-to-equity ratio;
- Accruals;
- Sector index volatility;
- Interest rate;
- Gross National Product;
- Inflation rate;
- Market volatility;

Methods of dynamics of the state variable:

- `last`—no dynamics of x;
- `diff`—first-difference of x;
- `random`—an unobserved component of time series decomposition of x;
- `roll.sd`—moving 8 quarters standard deviation of x;

Data and experimental setup

Databases:

- Analysts' Price targets data from ThomsonOne I/B/E/S Detailed History;
- Stocks data from ThomsonOne DataStream:

Target rankings: Given a price target ξ, we, first define the forecast error (Δ) as an absolute value of the difference between actual price ξ_s and the price target made by an analyst k ($\hat{\xi}_{k,s}$):

$$\Delta_{t,k,s} = |\xi_{t,s} - \hat{\xi}_{t,k,s}| \tag{4}$$

Then, we calculate the average error across analysts as:

$$\overline{\Delta}_{t,s} = \frac{1}{k} \sum_{k=1}^{k} \Delta_{t,k,s} \tag{5}$$

Next, PMAFE is given as:

$$\tilde{\Delta}_{t,k,s} = \frac{\Delta_{t,k,s}}{\overline{\Delta}_{t,s}} \tag{6}$$

Different information sets:

- *recent* uses only the information about the analyst's performance in period $t-1$;
- *all-time* uses all the available information for that particular analyst.
- *true* assumes we anticipate perfectly the future analyst accuracy performance that would only be available at the end of t

Figure