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Combining forecasts to predict the outcome of horseraces

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Section 2-2-F

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Outline

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Competitive Event (CE) Prediction

- Definition
  Scenario where multiple participants compete against each other for some reward

- Prediction task
  - Estimate participants' chances of winning
  - Evaluate the relative importance of factors that govern CE outcome

- Examples (e.g., elections, sports events)

46%

vs.

54%

vs.

Win: 71%
Draw: 28%
Lose: 1%

21%

26%

17%

13%

...

Competitive Event (CE) Prediction

- Several statistical methods have been employed to predict probabilities in CEs (e.g., ANN, SVM, decision trees etc.).
  - *But fail to account for the intensity of competition.*
- Pooling of statistical forecasts is effective in many other domains.
  - But the combination of statistical forecasting models in CEs has been neglected.

Research objective

- Develop a methodology for combining model-bases predictions in CEs.

Contributions

- Demonstrate how a library of **diverse** and **accurate** base forecasts can be constructed in **CEs**.
- Establish that average-based forecast pooling (employed in many other domains) is **in**effective in CEs.
- Develop a mechanism for forecast combination (**stacking**) which meets the requirements and exploits the peculiarities of CEs.

Modeling Competitive Events

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Choice modeling approach: ***Conditional logit regression***

- Interpretation: View competitors as alternatives **within a choice set** and the winner as the participants whose credentials have resulted in it being the **preferred alternative**.

- Formula:

  - p_i^j Winning probability of participant i in event j
  - $\boldsymbol{x}_i^j$ Participant characteristics (i.e., independent variables)
  - $\boldsymbol{\beta}$ Regression coefficients to be estimated
  - m_j Number of participants in event j

$$p_i^j = \frac{\exp\left(\boldsymbol{\beta} \cdot \boldsymbol{x}_i^j\right)}{\sum_{i=1}^{m_j} \exp\left(\boldsymbol{\beta} \cdot \boldsymbol{x}_i^j\right)}$$

[McFadden, 1974]

Modeling Competitive Events

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- Conditional logit regression:

Account for competition element within CEs.

Ability of participant i

$$p_i^j = \frac{\exp\left(\boldsymbol{\beta} \cdot \boldsymbol{x}_i^j\right)}{\sum_{i=1}^{m_j} \exp\left(\boldsymbol{\beta} \cdot \boldsymbol{x}_i^j\right)}$$

… normalized by the strengths of its opponents in event j

[McFadden, 1974]

Forecast Combination

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- Essence of forecasting ensemble
  - Build a (large) library of **strong** and yet **diverse** *base models*
  - **Combine** predictions in some manner

Forecast Combination

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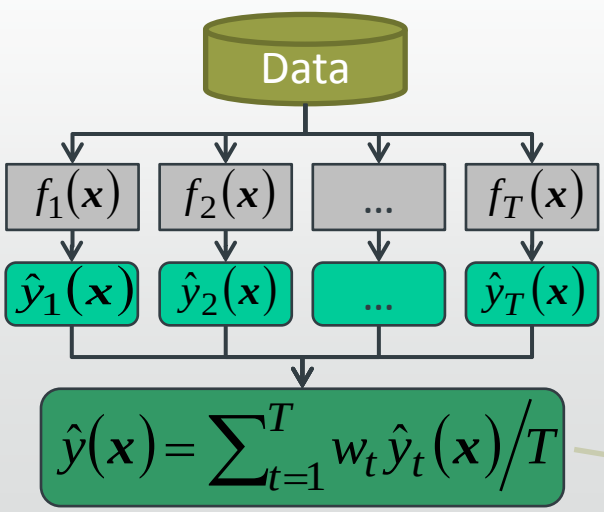
- Base models generation: Three-level approach

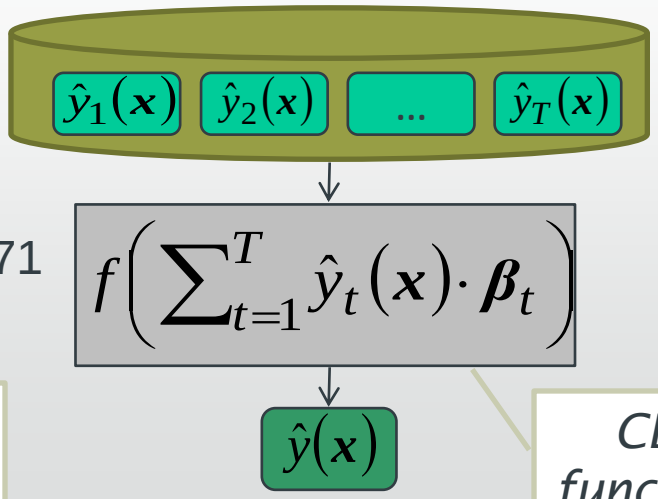
1. **Define** surrogate measures of **event outcome** to translate prediction tasks into 'ordinary' modeling objectives (continuous: 'finishing position in horseracing' or discrete: 'win or loss')
2. Forecast resulting dependent variables with alternative **prediction methods** (regression & classification)
3. Vary **meta-parameter settings** of these methods

Two Forecast Combination Schemes

- **Average**-based combination
  - Problem: Complicated by surrogate objectives
  - Overcome: Develop forecast **calibration** algorithm (Platt, 2000)
- **Stacking**-based combination
  - 'Learn' combination rule empirically
  - CL can be employed to combine base forecasts: **LLR-based selection**



Note: T = 571



Weighted function

CL function

Research question

- To assess the accuracy of composite forecasts resulting from **average-** and **stacking-**based pooling mechanisms.

Horseracing data

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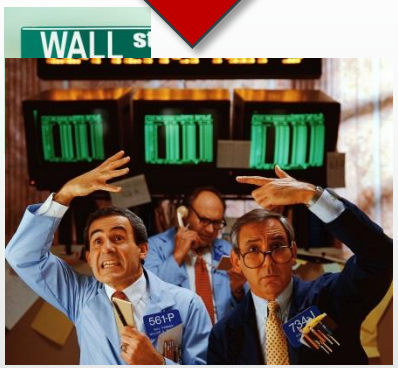
- **Many similarities with wider financial markets**
  - Ease of market entry
  - Numerous diverse participants
  - Widespread availability of information
  - Multiple factors affect assets' values
  - Similar behavioral biases among traders
- **Difficult benchmark**
  - Renowned as efficient markets
  - Number of participants varies between events.



→ **Betting markets are routinely used to shed light on decision maker's behavior in wider financial markets**

Experimental Design

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- Data & variables (Bolton & Chapman, 1986)
  - 4,276 horseraces run in Hong Kong (55,690 runners)
  - Past performance (runners/jockeys) & race conditions
- Model evaluation
  - Split-sample setup (65% : 35%)
  - 5-fold cross validation on in-sample data
- Measures of forecasting performance
  - Coefficient of determination, R^2
  - Rate of return when betting on model predictions using Kelly 's (1956) investing strategy.
- Base models

  By varying dependent variable measures, predictions methods, and meta-parameter values, a library of 571 individual base models is produced.

Empirical Results

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- Average-based forecast combination

	Ensemble member	R^2	Rate of return	p-value*
Benchmark model (conditional logit)	CL base model Track probabilities	0.1532	10.84	0.1386
Simple average	All base models Track probabilities	0.1003	-8.44	0.9480
Optimal trimmed simple average	CL base model Track probabilities	0.1531	10.80	0.0693
Weighted average	CL base model Track probabilities Support vector regression	**0.1538**	**11.25**	0.0938

* Statistical test of H_0: return > 0

Forward-selection of base models (Caruana et al., 2006).
Weights are decided by no. of times the models enter the ensemble

Empirical Results

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- Stacking-based forecast combination (conditional logit stacking model)

	Ensemble size*	R^2	*p*-value**	Rate of return	*p*-value***
Benchmark model	2	0.1532	/	10.84	0.1386
CL stacking model: LLR-based variable selection	5	**0.1543**	0.0432	**20.31**	0.0149
CL stacking model: best models per modeling objective	5	0.1538	0.1933	16.16	0.0505
CL stacking model: best models per method	10	0.1540	0.6561	17.67	0.0399

* Number of base models selected for the ensemble
** LLR-test of benchmark model vs. ensemble model
*** Statistical test of H_0: return > 0

Conclusions

- Forecast combination improves accuracy
- Standard combination scheme (averages) less suitable due to competition
- Stacking through 2nd stage cond. logit model superior
- Novel analytical tool to study competitive events

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Questions & comments?

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