Behavioural analytics

Exploring behavioural patterns in large datasets

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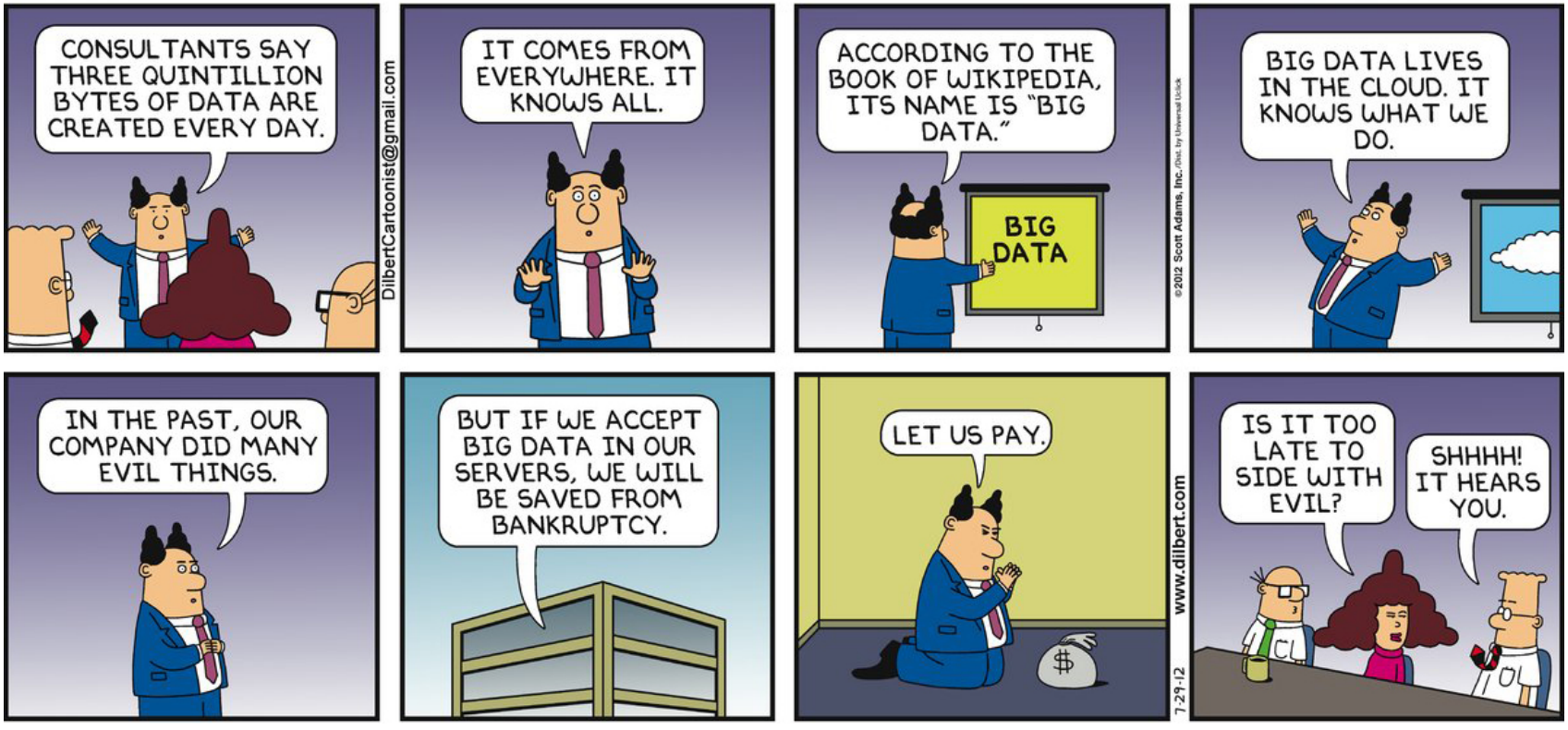
Big data, analytics, data science



Unprecedented data on human judgment and decision making

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What opportunities are there for operations research?

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What opportunities are there for operations research?

What typical kinds of problems are there?

Data: 8.7 million predictions of outcomes of 124 Super 15 rugby games

Predictions consist of a winner and winning margin

Three case studies

Crowd wisdom in sports forecasts

- "Wisdom of the crowd"
- How much crowd wisdom is there?
- For each game, compare Absolute Crowd Error and Mean Absolute Individual Error

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ACE smaller than MAIE in 70% of games

ACE on average 32% smaller than MAIE

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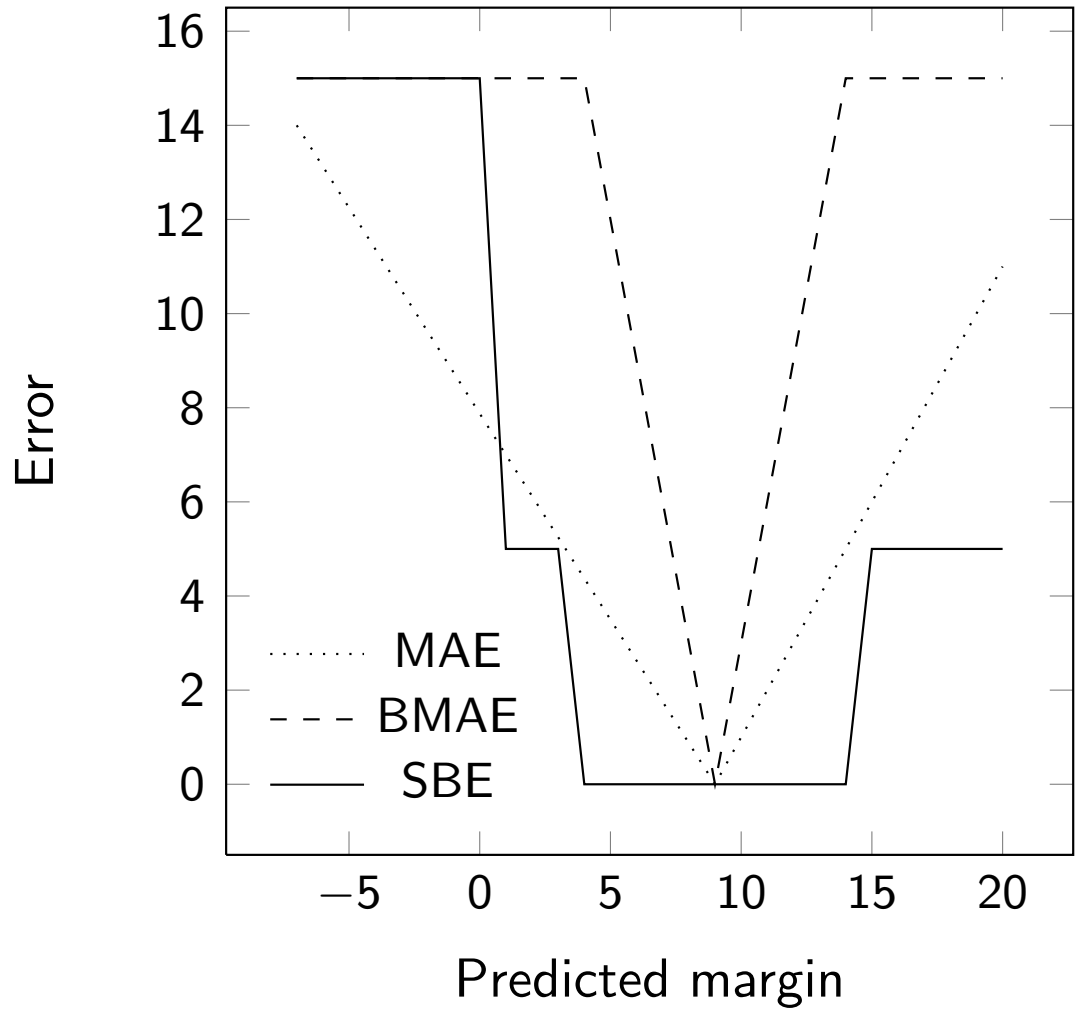
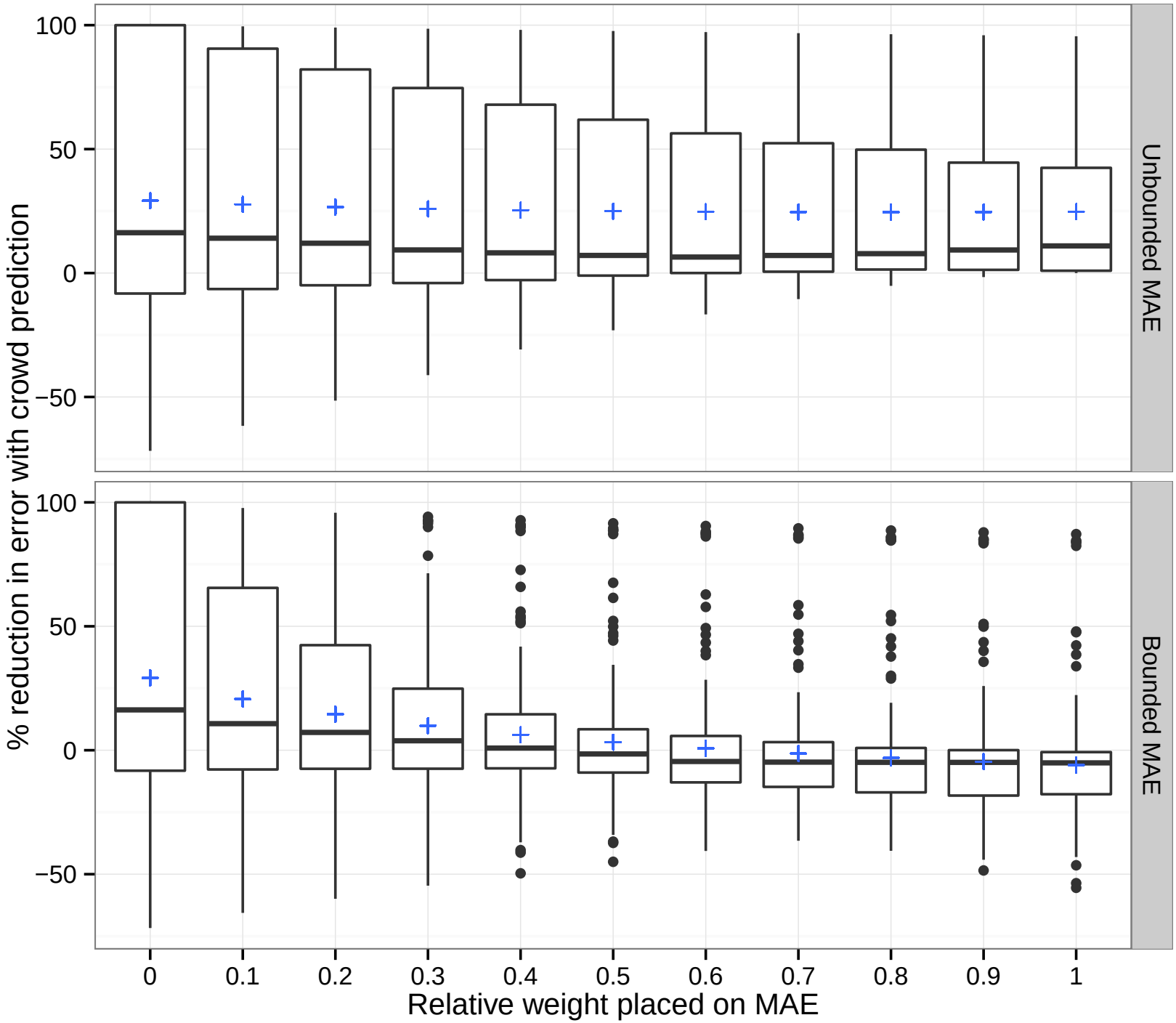
What about other loss functions?

Loss functions used to evaluate judgments



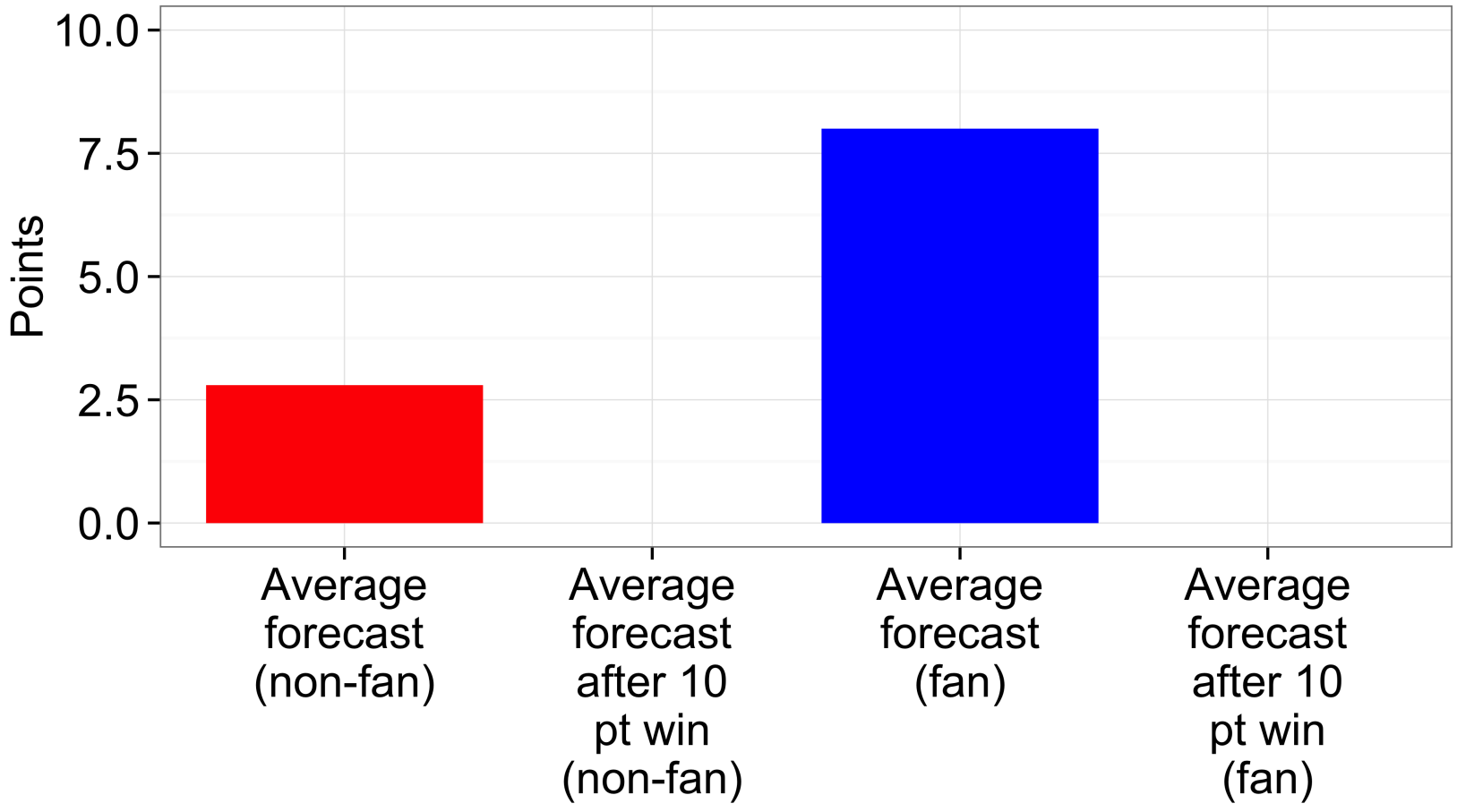

% reduction in error with crowd prediction
100
50
0
−50
Unbounded MAE
Bounded MAE
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Relative weight placed on MAE

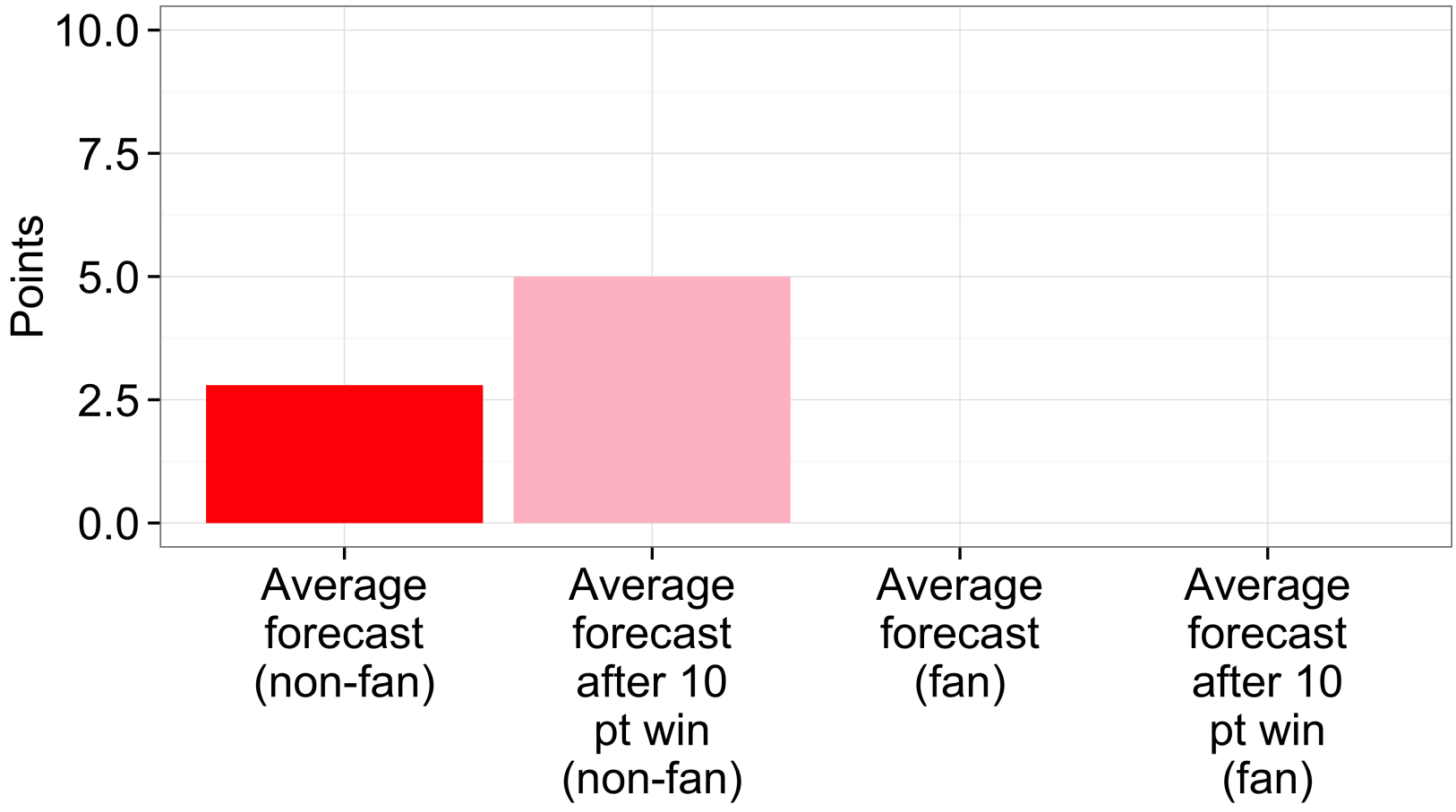
Crowd wisdom heavily dependent on choice of loss function

Affective responses in sports forecasts

Are these rational forecasters?

- Aim: quantify the magnitude of fan bias
- Hypothesis 1 – positive fan bias
- Hypothesis 2 – fans less sensitive to past performance


10.0
7.5
5.0
2.5
0.0
Points
Average forecast (non-fan)
Average forecast after 10 pt win (non-fan)
Average forecast (fan)
Average forecast after 10 pt win (fan)


10.0
7.5
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Points
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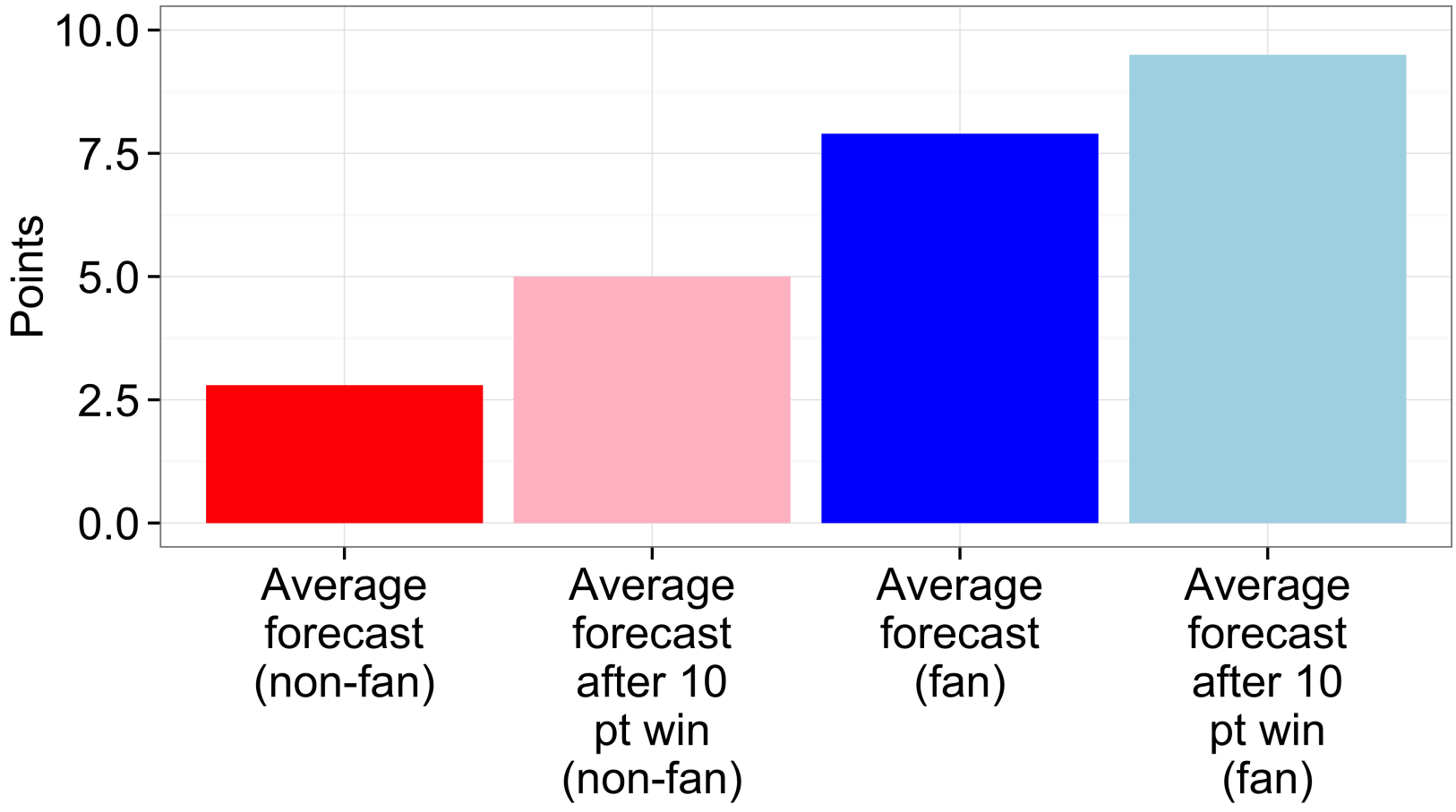
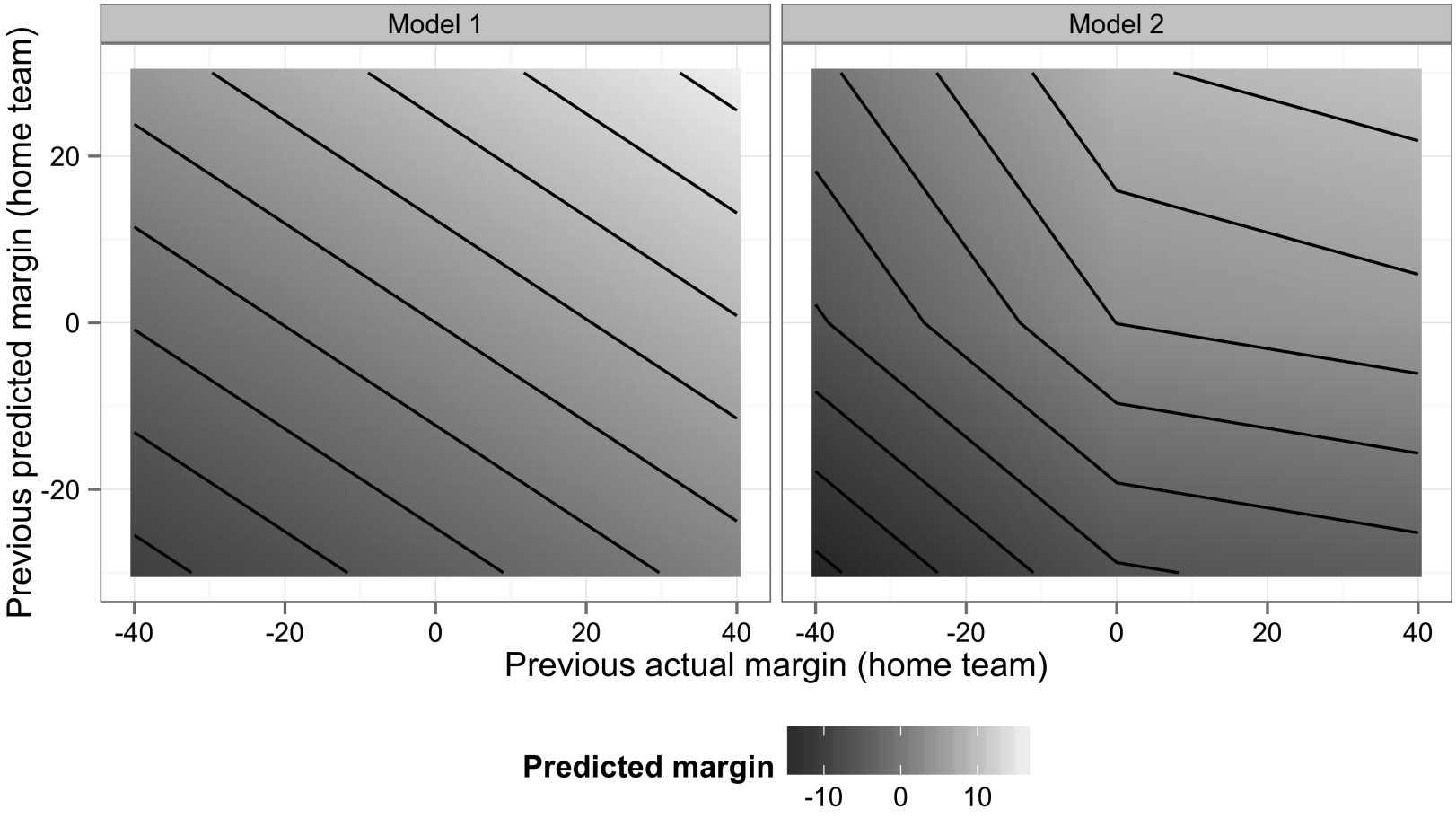

Points
10.0
7.5
5.0
2.5
0.0
Average forecast (non-fan)
Average forecast after 10 pt win (non-fan)
Average forecast (fan)
Average forecast after 10 pt win (fan)

Fans bias $\approx 200\%$

"Win elasticity" $\approx 20\%$ (non-fans)
vs. 15% (fans)

How do unexpected events affect forecasts?


Model 1
Model 2
Previous predicted margin (home team)
20
0
-20
-40
-20
0
20
40
Previous actual margin (home team)
Predicted margin
-10
0
10

Past predictions $>$ past performance

Losses loom larger than wins

Big losses loom especially large

six key streams

cognitive biases, prospect theory, intertemporal choice, debiasing, heuristics, collective judgments

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three key modes

detecting, exploiting, improving

three key modes

detecting, exploiting, improving

three key modes

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detecting, exploiting, improving

Streams	Detect	Exploit	Improve
Cognitive biases	✓	✓	✗
Prospect theory	✓	✓	✗
Intertemporal choice	✓	✓	✗
Debiasing	✗	✗	✓
Heuristics	✓	✓	✗
Collective judgments	✓	✓	✓

thank you

acknowledgements

Superbru (www.superbru.com), Online Skill Ltd.