Relevance-based prediction:

A transparent and adaptive alternative to machine learning

David Turkington
Co-authors: Megan Czasonis and Mark Kritzman

Relevance-based prediction: Overview

- **Relevance-based prediction** is a new forecasting routine that forms a prediction as a weighted average of observed outcomes that vary through time or cross-sectionally, in which the weights are based on a precise statistical measure called relevance.
    - Relevance has two components, **similarity and informativeness**, which are both measured as Mahalanobis distances.
- Relevance-based prediction depends crucially on **fit**, which measures the **average alignment of relevance and outcomes** across all the observations that go into a prediction.
    - Fit reveals the **confidence** one should assign to an individual prediction.
    - Fit also identifies the **optimal combination of observations and predictive variables** for each individual prediction task.

Key advantages of relevance-based prediction

- Relevance-based prediction **addresses complexities**, such as asymmetry between predictive variables and outcomes, that are **beyond the capacity of linear regression analysis**.

- Relevance-based prediction is **more transparent and more adaptive** than model-based machine learning algorithms, and it is **theoretically justified**.

- Relevance-based prediction is a sophisticated extension of model-free machine learning algorithms, that uniquely **converges to linear regression analysis** under special circumstances.

The task: Predict Y given X

Model-based approach

Posit a model (prediction function and set of parameters) that will be used for every prediction task.

Estimate the parameters based on prior observations, and then discard the observations.

Model-free approach

For a ***specific prediction task***, determine how much weight to place on each prior observation.

Extract as much information as needed from the pertinent observations.

The task: Predict Y given X

Model-based approach

$$y = f(x)$$

$$estimate\ f(x)\ using\ X, Y$$

$$\hat{y}_t = f(x_t)$$

EXAMPLES:
Linear regression, Lasso
Decision trees, random forest
Neural networks, transformers

Model-free approach

$$\hat{y}_t = \sum_i w_{it} y_i$$

$$choose\ w_{it} = g(x_t, X, Y)$$

EXAMPLES:
Nearest neighbors
Kernel regression
Relevance-based prediction

Learning from new observations: Three methods

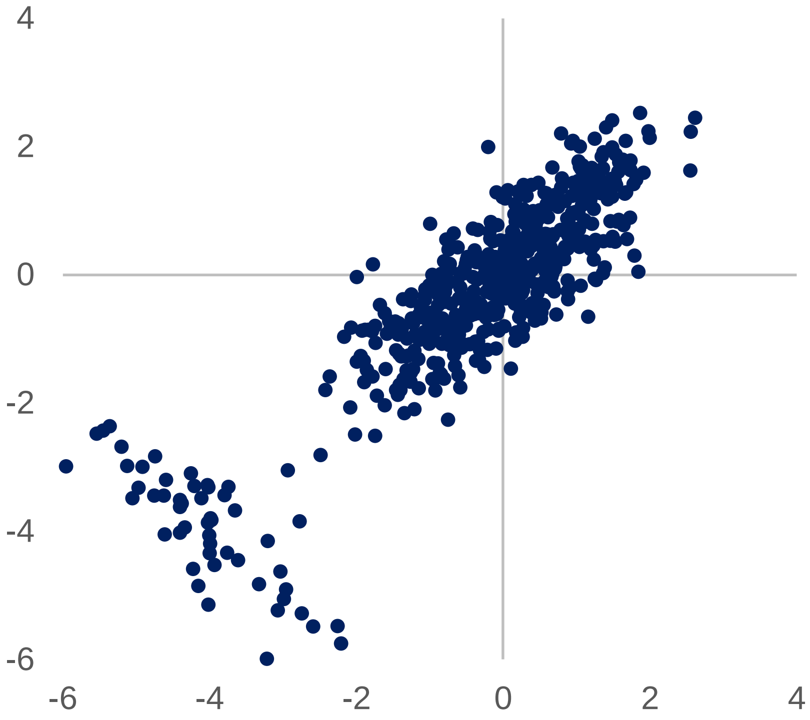
1. **Retrain completely**
   Recompute the model's parameters from scratch using all data (including new data)

2. **Online learning**
   Incrementally update the model's parameters at a defined "learning rate"

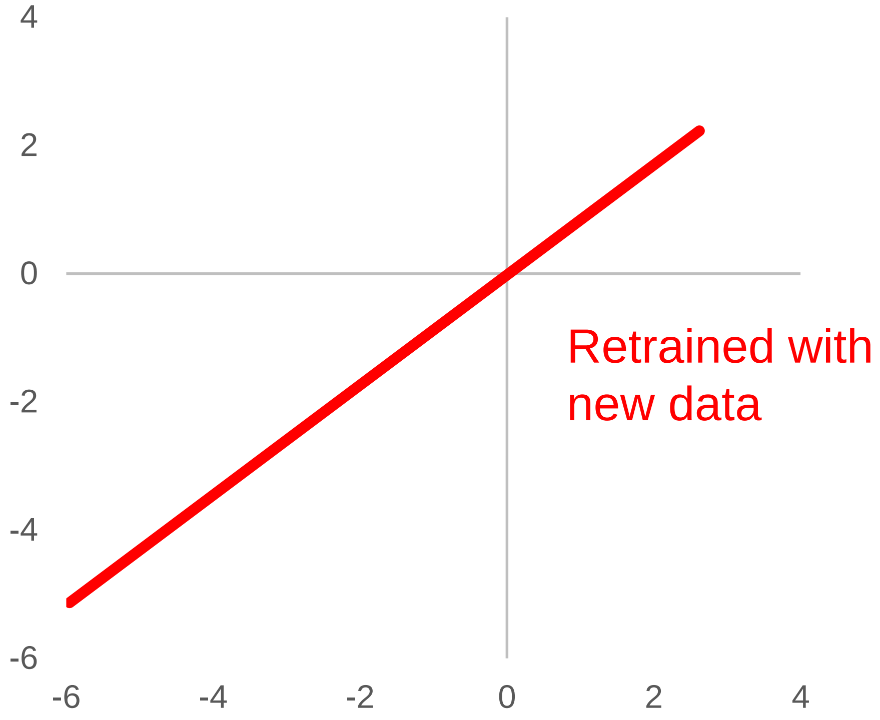
3. **Model-free adaptive learning**
   Dynamically retrieve new data as needed for each prediction task

Example: (1) Complete retraining

Observed data



Model view ($\beta = 0.86$)

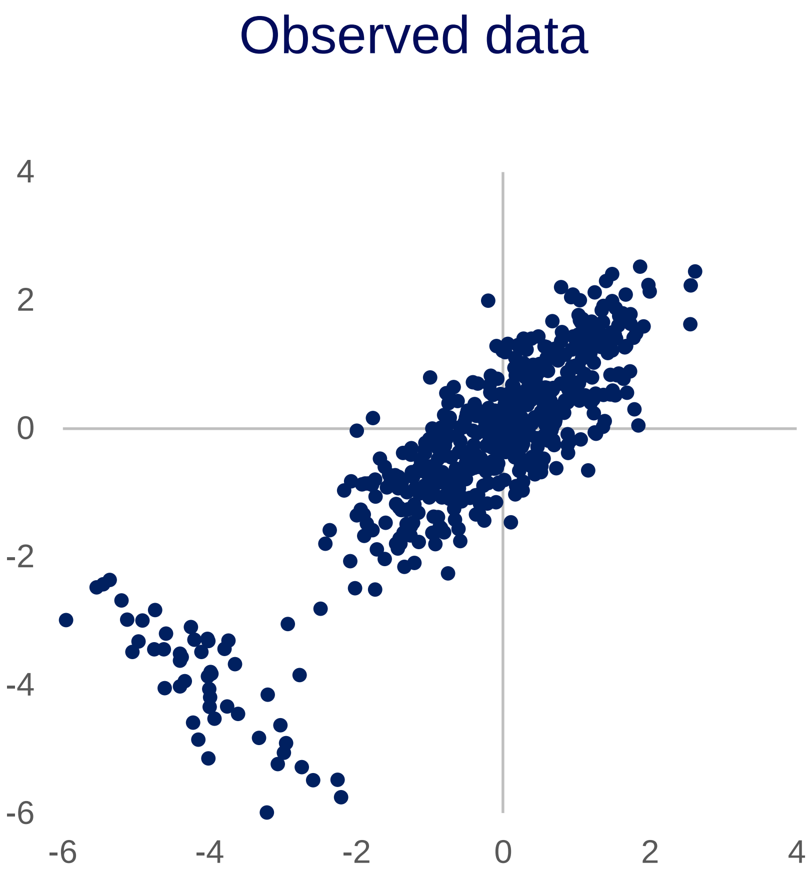


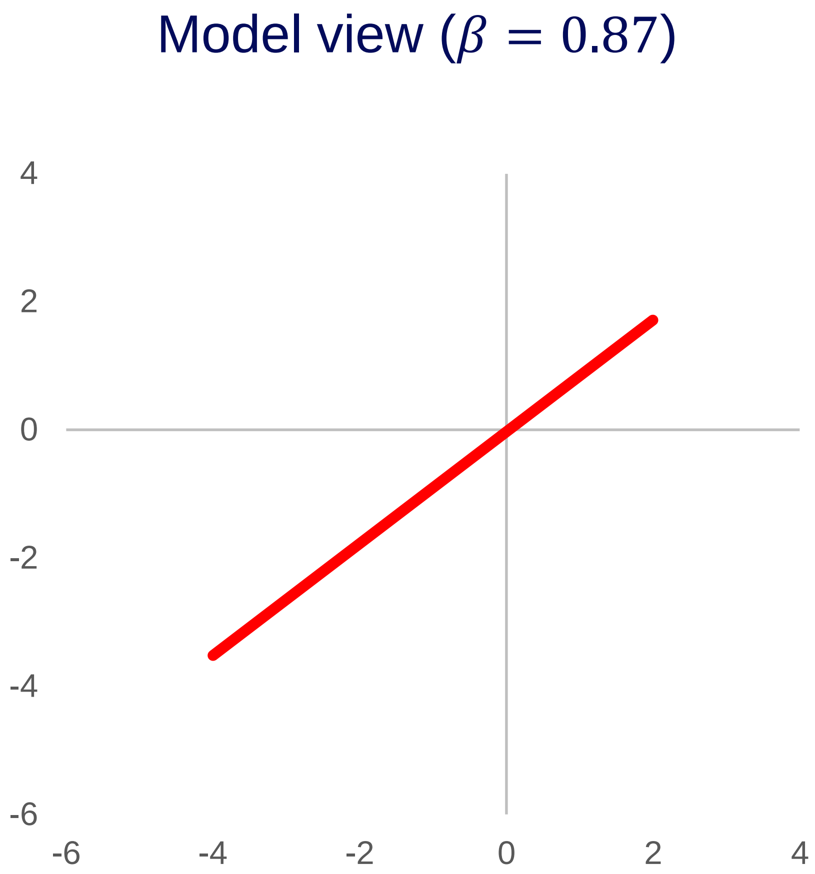
Retrained with new data

For illustration only. The original observations are 500 random draws of two variables with 0.8 correlation, and additional observations are 50 random draws of two variables with -0.9 correlation. The learning rate (alpha) equals 1/500. Source: State Street Global Markets.

Example: (2) Online learning

Update rule: $\beta_{new} = \beta_{old} + \alpha(y_\tau - \hat{y}_\tau)x_\tau$





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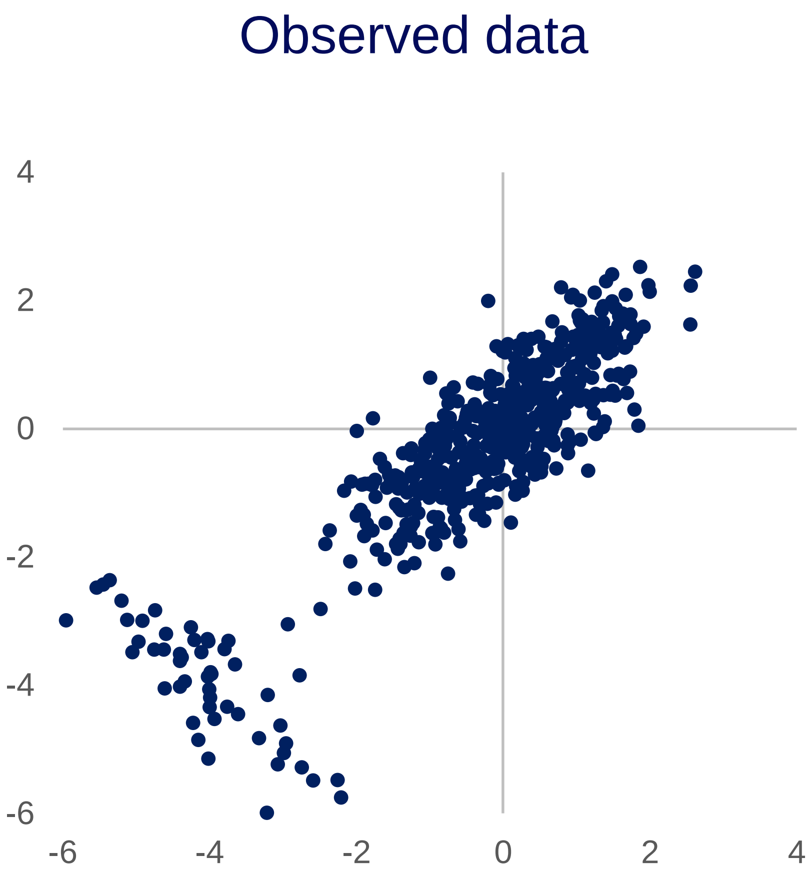
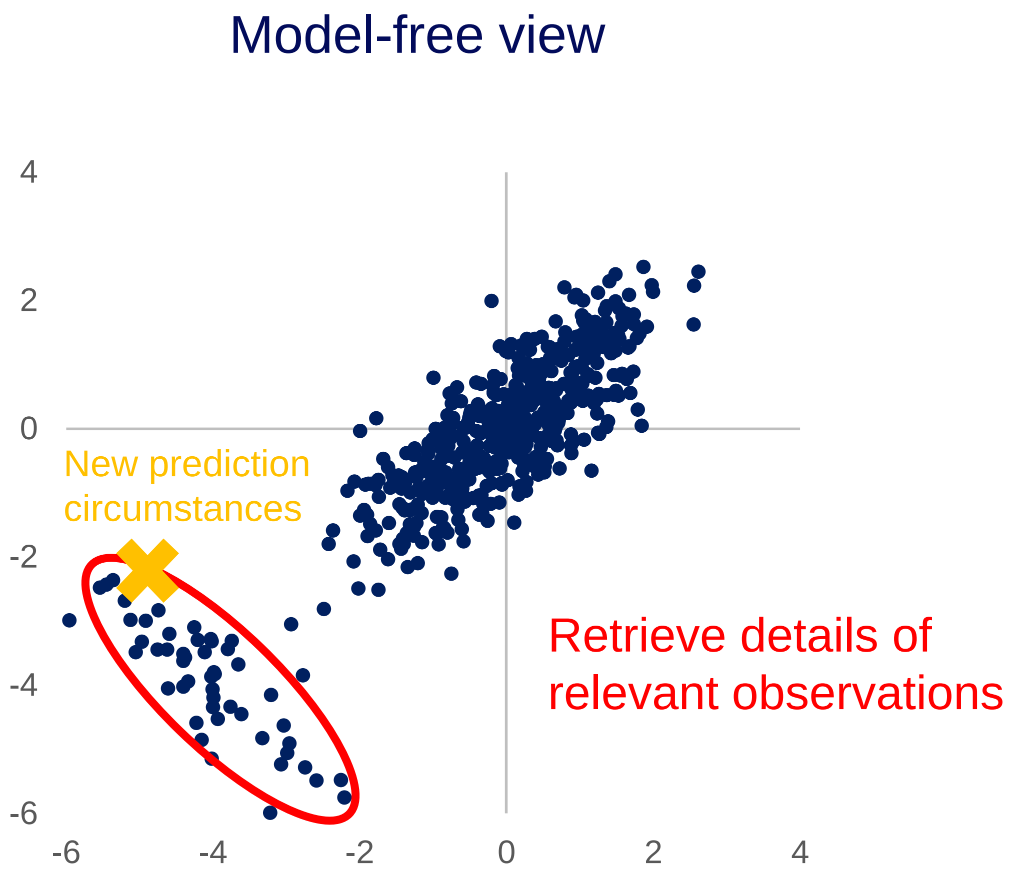
Example: (3) Model-free adaptive learning



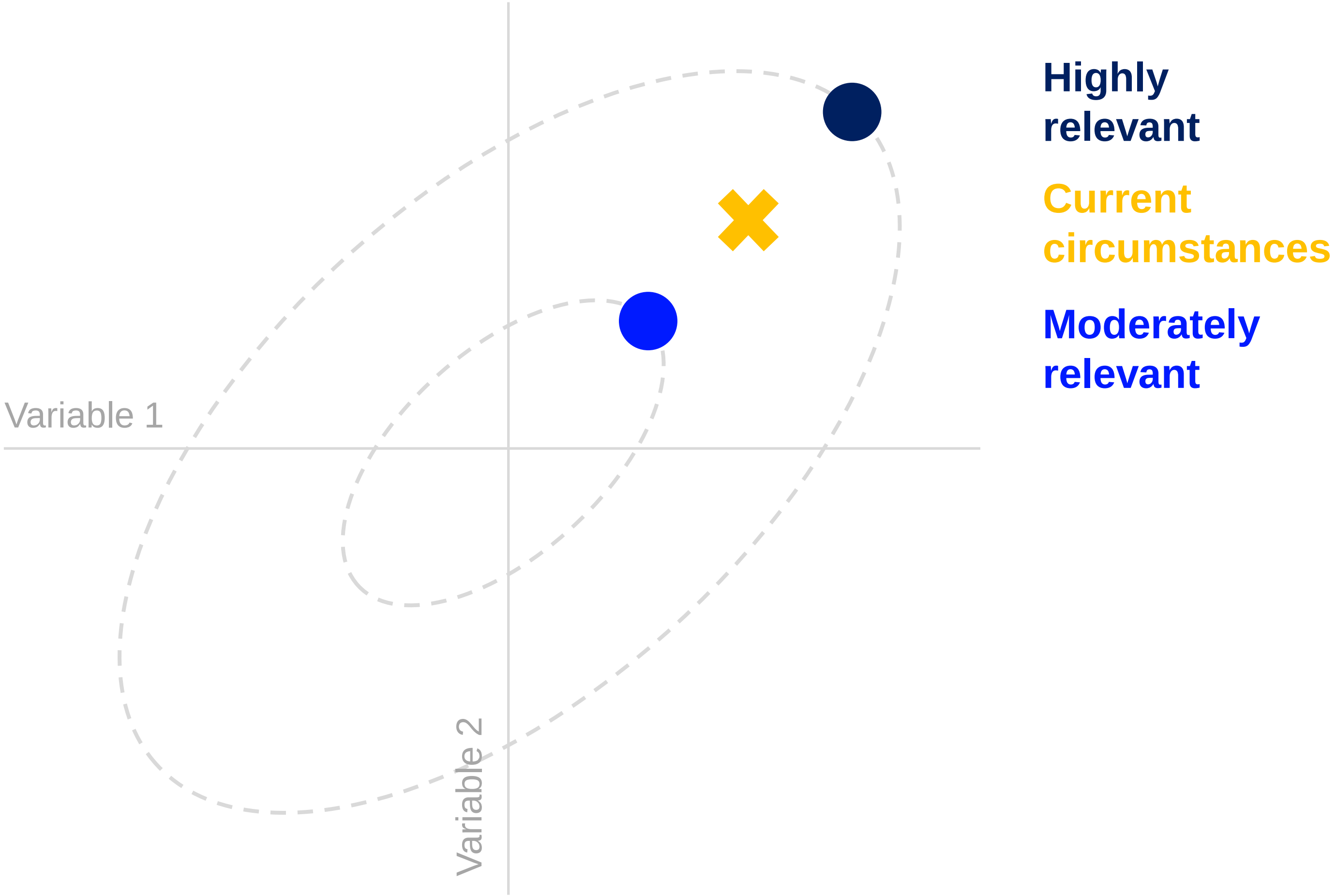


For illustration only. The original observations are 500 random draws of two variables with 0.8 correlation, and additional observations are 50 random draws of two variables with -0.9 correlation. The learning rate (alpha) equals 1/500. Source: State Street Global Markets.

Relevance

What is a principled way to determine relevance?

- A past observation is relevant to current prediction circumstances to the extent that it is:
  - **Similar to current circumstances,** and
  - **Different from average**



For illustration only. Source: State Street Global Markets.

Relevance: Precise multivariate definition

The relevance of an observation (x_i) to a prediction circumstance (x_t) is:

$$r_{it} = sim(x_i, x_t) + \frac{1}{2}\left(info(x_i, \bar{x}) + info(x_t, \bar{x})\right)$$

$sim(x_i, x_t) = -\frac{1}{2}(x_i - x_t)\Omega^{-1}(x_i - x_t)'$	Observation's proximity to current circumstances
$info(x_i, \bar{x}) = (x_i - \bar{x})\Omega^{-1}(x_i - \bar{x})'$	Observation's distance from average
$info(x_t, \bar{x}) = (x_t - \bar{x})\Omega^{-1}(x_t - \bar{x})'$	Centers relevance around zero

Why relevance is not arbitrary (Part 1: information theory)

- **Information theory** tells us that the information in an observation is the negative logarithm of its likelihood.

$$information(x_i) = -\log(p(x_i))$$

Sum	Total possibilities	With this sum	Probability	**Information** (base 10)
100	10,000,000,000	1	0.0000000001	10
99	10,000,000,000	10	0.0000000010	9
98	10,000,000,000	55	0.0000000055	8.26
…				

For illustration only. Source: State Street Global Markets.

Why relevance is not arbitrary (Part 1: information theory)

- **Information theory** tells us that the information in an observation is the negative logarithm of its likelihood.

$$information(x_i) = -\log(p(x_i))$$

- It also tells us that the normal distribution has **maximum entropy** for a given variance.

$$p_{normal}(x_i) \propto e^{-\frac{1}{2}(x_i - \bar{x})\Omega^{-1}(x_i - \bar{x})'}$$

- In addition, the **Central Limit Theorem** motivates the normal distribution as a common limiting case of many random processes.

- The **Mahalanobis distance** measures the information in a multivariate normal observation (or between a pair of observations).

$$information(x_i) \propto (x_i - \bar{x})\Omega^{-1}(x_i - \bar{x})'$$

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- **Information theory** tells us that the information in an observation is the negative logarithm of its likelihood.
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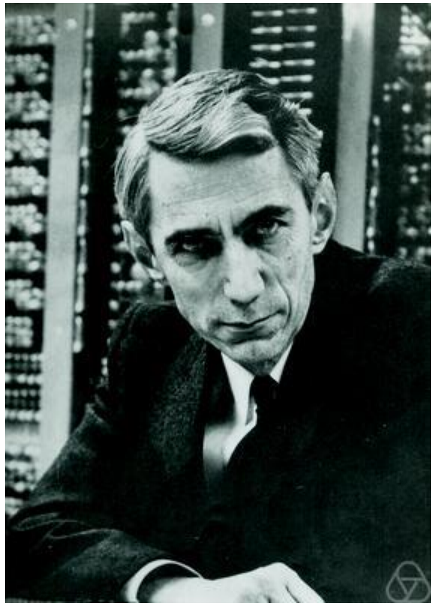

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Why relevance is not arbitrary (Part 2: linear regression equivalence)

- Relevance values sum to zero and tilt around equal weights.
- Recall that we form a prediction as a weighted average of past outcomes.
- **The prediction matches linear regression** (OLS) if we include every observation in our data sample.

$$w_{it,lin} = \frac{1}{N} + \frac{1}{N-1} r_{it}$$

$$\hat{y}_t = \sum_{i=1}^{N} w_{it} y_i$$

$$\left.\begin{aligned} \hat{y}_{t,lin} &= \bar{y} + \sum_{i=1}^{N} r_{it}(y_i - \bar{y}) \\ \hat{y}_{t,lin} &= \alpha + x_t \beta \end{aligned}\right\} \text{Equal}$$

Why relevance is not arbitrary (Part 2: linear regression equivalence)

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- **The prediction matches linear regression** (OLS) if we include every observation in our data sample.

Source: Public domain image of portrait by Christian Albrecht Jensen.

Partial sample regression

This equivalence with linear regression reveals an intriguing insight:

Linear regression places as much importance on non-relevant observations as on relevant ones.

It just changes the sign of their effect.

Partial sample regression

- **Partial sample regression** forms a prediction from a subset of the most relevant observations.
- We may write the prediction equivalently in terms of weights that sum to one.
- **Predictions are no longer linear** with respect to prediction circumstances (x_t). Censoring introduces nonlinear conditionality.

$$\hat{y}_{t,psr} = \bar{y} + \frac{\lambda^2}{n-1}\sum_i \delta(r_{it}) r_{it}(y_i - \bar{y})$$

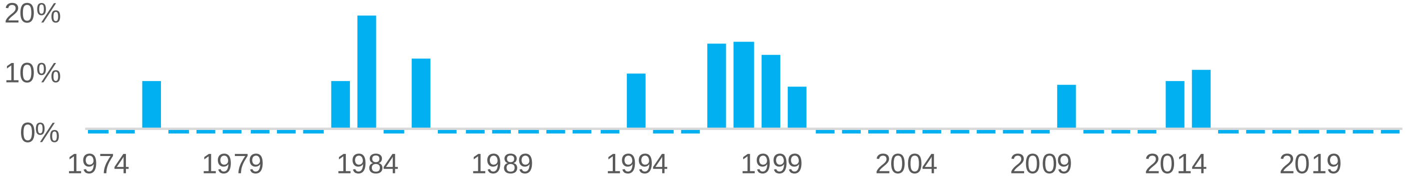
$$w_{it,psr} = \frac{1}{N} + \frac{\lambda^2}{n-1}\left(\delta(r_{it}) r_{it} - \varphi \bar{r}_{sub}\right)$$

DEFINITIONS: $\delta(r_{it}) = 1\ if\ r_{it} > r^*, else\ 0$

$$n = \sum_i \delta(r_{it}) \qquad \bar{r}_{sub} = \frac{1}{n}\sum_i \delta(r_{it}) r_{it}$$

$$\varphi = \frac{n}{N} \qquad \lambda^2 = \frac{\sigma^2_{r,full}}{\sigma^2_{r,partial}} = \frac{\frac{1}{N-1}\sum_i r_{it}^2}{\frac{1}{n-1}\sum_i \delta(r_{it}) r_{it}^2}$$

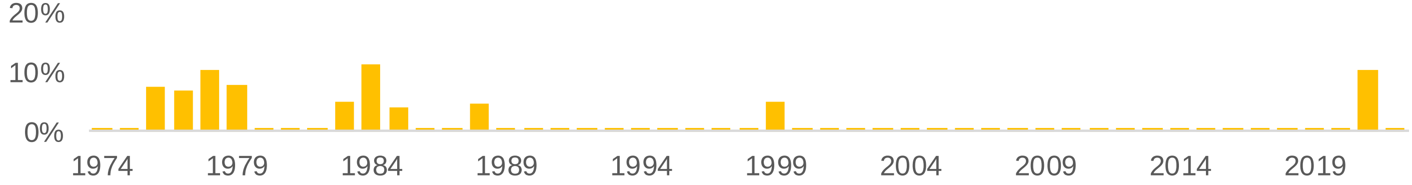
Economic example: Partial sample prediction weights (inflation & growth)



Robust

Inflation = 0.9%

Real growth = 4.5%



Overheated

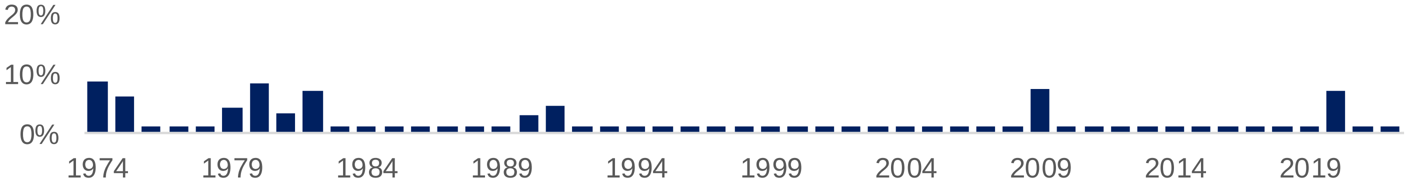
Inflation = 5.0%

Real growth = 4.5%

Slowdown

Inflation = 0.9%

Real growth = 1.9%



Stagflation

Inflation = 5.0%

Real growth = 0.9%

Notes: Weights are based partial sample regression using the 25% most relevant observations between 1974 and 2022. Inflation and real growth data are obtained from the FRED data website.
Source: “Portfolio Construction When Regimes Are Ambiguous” by Kritzman, Kulasekaran and Turkington.

Binary weights versus partial sample weights

Binary weights

- It is typical to define regimes as **binary occurrences** based on a **single indicator** and to estimate regime outcomes by equally weighting their values across the regime periods.
- This binary approach assumes that all regime **periods are equally useful** in predicting outcomes.
- It precludes using more than one indicator in a principled way, and it risks producing **empty regimes**.

Partial sample weights

- **Partial sample prediction** instead weights past outcomes by the **relevance** of each regime period.
- Relevance reflects the extent to which a period aligns with a **regime's prototypical circumstances**.
- It allows a period to be connected to **more than one regime**.
- And it enables us to consider regimes that have **never occurred** historically.

Fit

Fit

- Fit reveals how much confidence we should attach to a **specific prediction task**, separately from the overall confidence we have in the associated prediction routine.

- Fit is equal to the squared correlation between observation weights and outcomes.

$$fit_t = \rho(w_t, y)^2$$

- Note that this calculation is only possible because we know each observation’s contribution to the prediction.

Why relevance is not arbitrary (Part 3: R-squared equivalence)

- For a full-sample linear regression, the informativeness-weighted average fit across all prediction tasks equals the classical R^2 statistic.

$$R^2 = \frac{1}{T-1}\sum_t info(x_t) fit_t$$

- The fit of each prediction can vary dramatically, which underscores the limitation of R^2 as a measure of confidence for an individual prediction.

Codependence

Using fit to optimize prediction-specific calibration

- For partial sample regression, rather than choose the censoring threshold r^* arbitrarily, we compute fit for a range of possible values and select the value that maximizes fit.

- Fit inherently balances small sample noise with subsample fit.

$$fit_{t,psr}(w) = \underbrace{\left(\frac{\varphi\lambda^2}{1-\varphi c^2}\right)}_{\text{Noise}} \underbrace{\frac{N}{N-1}\frac{n-1}{n}}_{\text{Diagonal correction}} \underbrace{fit_t(\delta(r_t)r_t, y)}_{\text{Subsample fit}}$$

DEFINITIONS:

$$c^2 = \frac{\bar{r}^2_{sub}}{\sigma^2_{r,partial}}\frac{n}{n-1}$$

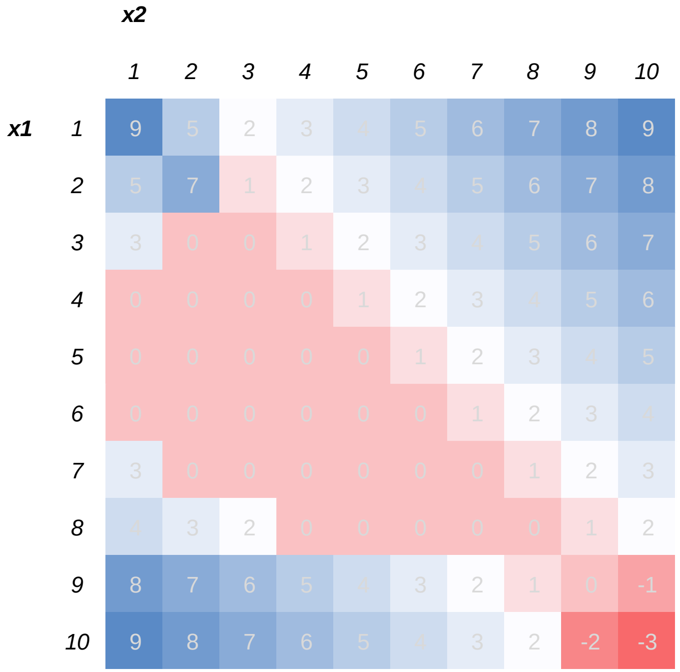
Codependence

- We may also use fit to select **prediction-specific** subsets of X variables.
- We maximize fit as a **joint function** of the choice of observations and the choice of variables.
- We refer to the prediction routine based on this joint maximization as **CKT regression**.
- **CKT regression** recognizes that the usefulness of observations and variables is **not static nor mutually independent**; it depends on the prediction task's unique circumstances.
  - **Lasso regression** selects variables but assumes a variable is useful always or never.
  - **Kernel regression** selects observations but assumes a static calibration.
  - Moreover, it is suboptimal to apply these selection techniques independently.

Empirical Illustrations

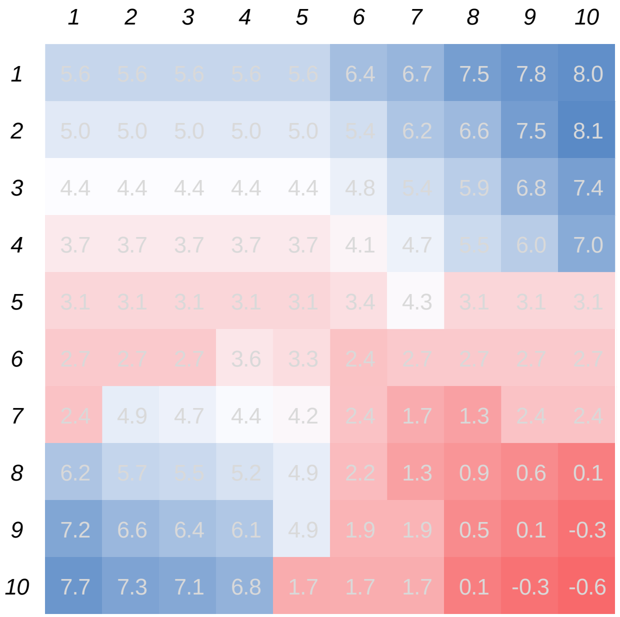
Toy example: Two predictive variables

Observed (contrived) data



		x2									
		1	2	3	4	5	6	7	8	9	10
x1	1	9	5	2	3	4	5	6	7	8	9
	2	5	7	1	2	3	4	5	6	7	8
	3	3	0	0	1	2	3	4	5	6	7
	4	0	0	0	0	1	2	3	4	5	6
	5	0	0	0	0	0	1	2	3	4	5
	6	0	0	0	0	0	0	1	2	3	4
	7	3	0	0	0	0	0	0	1	2	3
	8	4	3	2	0	0	0	0	0	1	2
	9	8	7	6	5	4	3	2	1	0	-1
	10	9	8	7	6	5	4	3	2	-2	-3

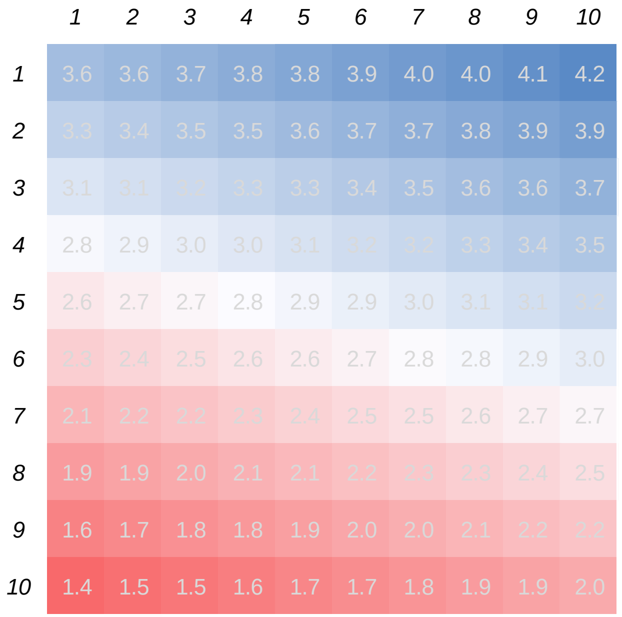
CKT predictions



	1	2	3	4	5	6	7	8	9	10
1	5.6	5.6	5.6	5.6	5.6	6.4	6.7	7.5	7.8	8.0
2	5.0	5.0	5.0	5.0	5.0	5.4	6.2	6.6	7.5	8.1
3	4.4	4.4	4.4	4.4	4.4	4.8	5.4	5.9	6.8	7.4
4	3.7	3.7	3.7	3.7	3.7	4.1	4.7	5.5	6.0	7.0
5	3.1	3.1	3.1	3.1	3.1	3.4	4.3	3.1	3.1	3.1
6	2.7	2.7	2.7	3.6	3.3	2.4	2.7	2.7	2.7	2.7
7	2.4	4.9	4.7	4.4	4.2	2.4	1.7	1.3	2.4	2.4
8	6.2	5.7	5.5	5.2	4.9	2.2	1.3	0.9	0.6	0.1
9	7.2	6.6	6.4	6.1	4.9	1.9	1.9	0.5	0.1	-0.3
10	7.7	7.3	7.1	6.8	1.7	1.7	1.7	0.1	-0.3	-0.6

*Correlation with actual: **73%***

Linear regression predictions



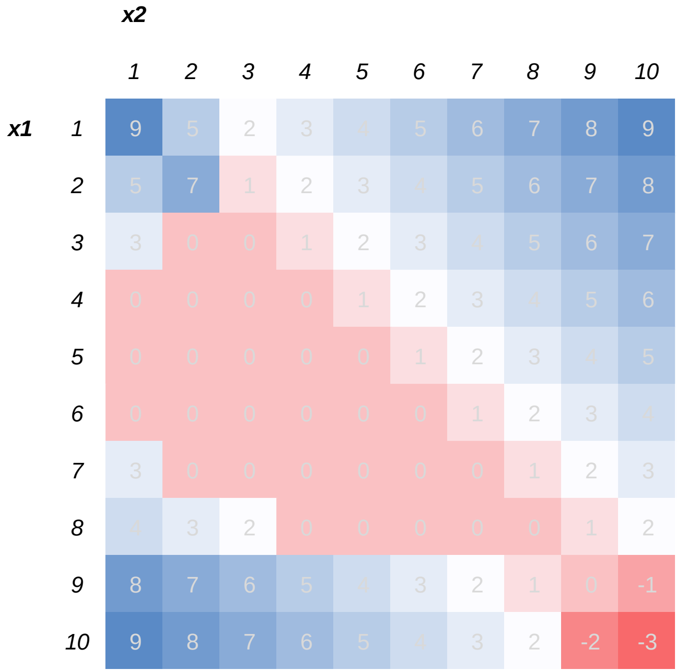
	1	2	3	4	5	6	7	8	9	10
1	3.6	3.6	3.7	3.8	3.8	3.9	4.0	4.0	4.1	4.2
2	3.3	3.4	3.5	3.5	3.6	3.7	3.7	3.8	3.9	3.9
3	3.1	3.1	3.2	3.3	3.3	3.4	3.5	3.6	3.6	3.7
4	2.8	2.9	3.0	3.0	3.1	3.2	3.2	3.3	3.4	3.5
5	2.6	2.7	2.7	2.8	2.9	2.9	3.0	3.1	3.1	3.2
6	2.3	2.4	2.5	2.6	2.6	2.7	2.8	2.8	2.9	3.0
7	2.1	2.2	2.2	2.3	2.4	2.5	2.5	2.6	2.7	2.7
8	1.9	1.9	2.0	2.1	2.1	2.2	2.3	2.3	2.4	2.5
9	1.6	1.7	1.8	1.8	1.9	2.0	2.0	2.1	2.2	2.2
10	1.4	1.5	1.5	1.6	1.7	1.7	1.8	1.9	1.9	2.0

*Correlation with actual: **26%***

For illustration only. Source: State Street Global Markets.

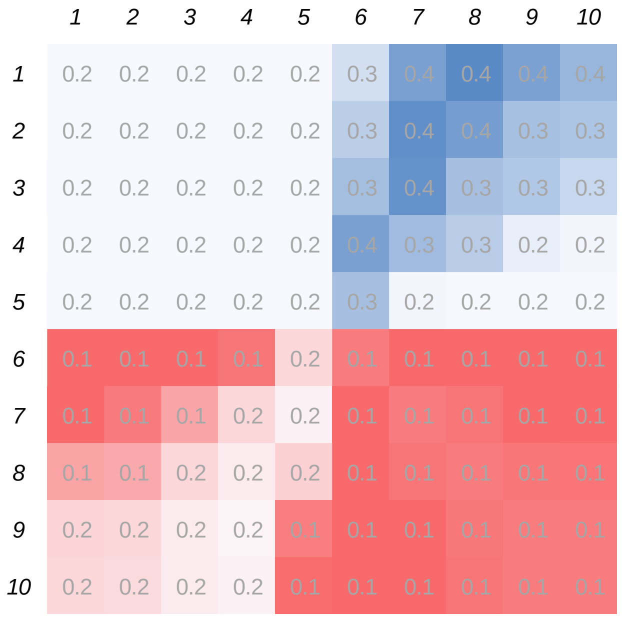
Toy example: Prediction-specific confidence

Observed (contrived) data



		x2									
		1	2	3	4	5	6	7	8	9	10
x1	1	9	5	2	3	4	5	6	7	8	9
	2	5	7	1	2	3	4	5	6	7	8
	3	3	0	0	1	2	3	4	5	6	7
	4	0	0	0	0	1	2	3	4	5	6
	5	0	0	0	0	0	1	2	3	4	5
	6	0	0	0	0	0	0	1	2	3	4
	7	3	0	0	0	0	0	0	1	2	3
	8	4	3	2	0	0	0	0	0	1	2
	9	8	7	6	5	4	3	2	1	0	-1
	10	9	8	7	6	5	4	3	2	-2	-3

Prediction-specific fits (CKT)

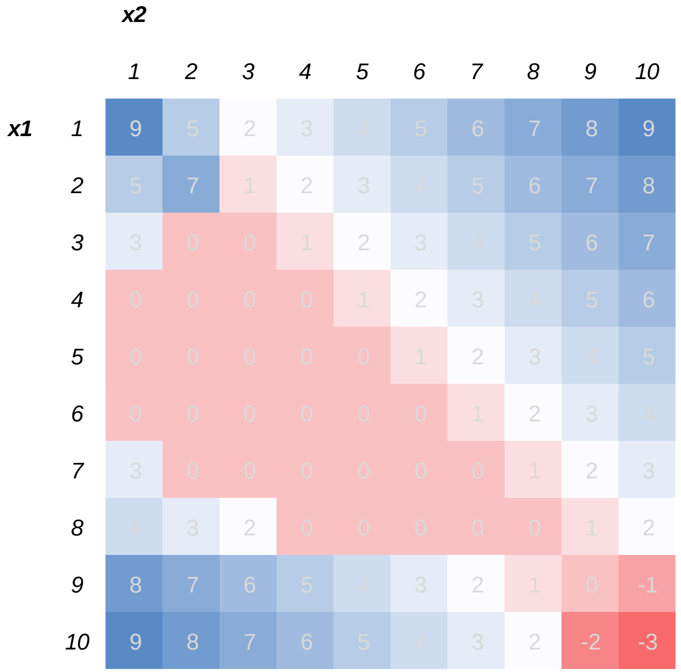


	1	2	3	4	5	6	7	8	9	10
1	0.2	0.2	0.2	0.2	0.2	0.3	0.4	0.4	0.4	0.4
2	0.2	0.2	0.2	0.2	0.2	0.3	0.4	0.4	0.3	0.3
3	0.2	0.2	0.2	0.2	0.2	0.3	0.4	0.3	0.3	0.3
4	0.2	0.2	0.2	0.2	0.2	0.4	0.3	0.3	0.2	0.2
5	0.2	0.2	0.2	0.2	0.2	0.3	0.2	0.2	0.2	0.2
6	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.1
7	0.1	0.1	0.1	0.2	0.2	0.1	0.1	0.1	0.1	0.1
8	0.1	0.1	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1
9	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1
10	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1

For illustration only. Source: State Street Global Markets.

Toy example: Codependent observation and variable selection

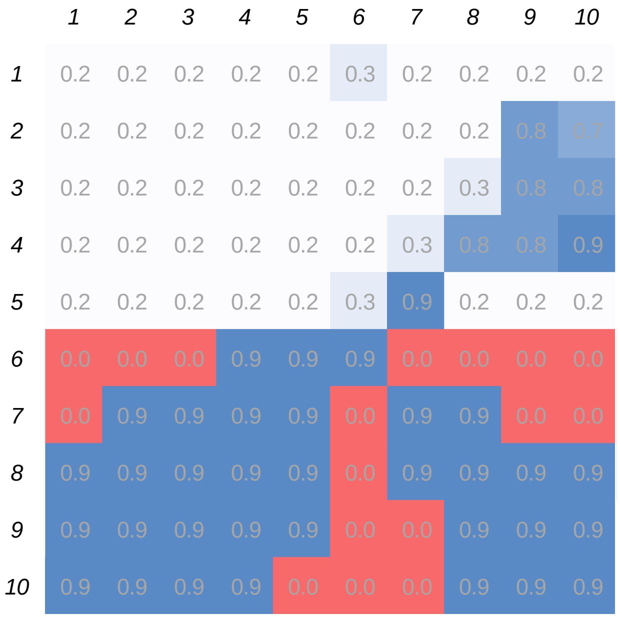
Observed (contrived) data



x2

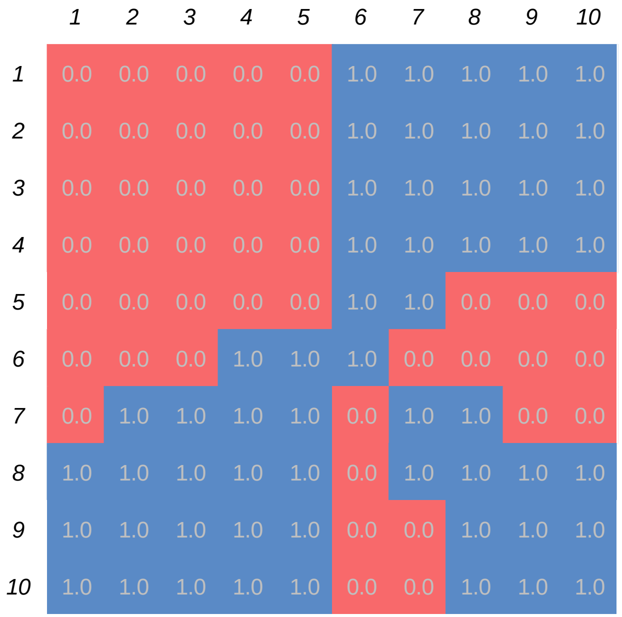
		1	2	3	4	5	6	7	8	9	10
x1	1	9	5	2	3	4	5	6	7	8	9
	2	5	7	1	2	3	4	5	6	7	8
	3	3	0	0	1	2	3	4	5	6	7
	4	0	0	0	0	1	2	3	4	5	6
	5	0	0	0	0	0	1	2	3	4	5
	6	0	0	0	0	0	0	1	2	3	4
	7	3	0	0	0	0	0	0	1	2	3
	8	4	3	2	0	0	0	0	0	1	2
	9	8	7	6	5	4	3	2	1	0	-1
	10	9	8	7	6	5	4	3	2	-2	-3

Prediction-specific r^*



	1	2	3	4	5	6	7	8	9	10
1	0.2	0.2	0.2	0.2	0.2	0.3	0.2	0.2	0.2	0.2
2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.8	0.7
3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.8	0.8
4	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.8	0.8	0.9
5	0.2	0.2	0.2	0.2	0.2	0.3	0.9	0.2	0.2	0.2
6	0.0	0.0	0.0	0.9	0.9	0.9	0.0	0.0	0.0	0.0
7	0.0	0.9	0.9	0.9	0.9	0.0	0.9	0.9	0.0	0.0
8	0.9	0.9	0.9	0.9	0.9	0.0	0.9	0.9	0.9	0.9
9	0.9	0.9	0.9	0.9	0.9	0.0	0.0	0.9	0.9	0.9
10	0.9	0.9	0.9	0.9	0.0	0.0	0.0	0.9	0.9	0.9

Prediction-specific inclusion of x2



	1	2	3	4	5	6	7	8	9	10
1	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0
2	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0
3	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0
4	0.0	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0
5	0.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0
6	0.0	0.0	0.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0
7	0.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	0.0	0.0
8	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0
9	1.0	1.0	1.0	1.0	1.0	0.0	0.0	1.0	1.0	1.0
10	1.0	1.0	1.0	1.0	1.0	0.0	0.0	1.0	1.0	1.0

For illustration only. Source: State Street Global Markets.

Regime simulation: Model assumptions

Assumptions

- Assume a Regime 1 with 80% persistence, and a Regime 2 with 60% persistence.
- In **Regime 1**, A and B are tightly distributed around a positive average and causally determine the outcome Y, while C and D contribute noise.
- In **Regime 2**, C and D are tightly distributed around a positive average and causally determine the outcome Y, while A and B contribute noise.
- A and B are 50% correlated, but independent of C and D. C and D are 50% correlated, but independent of A and B.
- The formula for Y is deterministic for a given regime, but the current regime is unknown and must be inferred from the predictive variables.

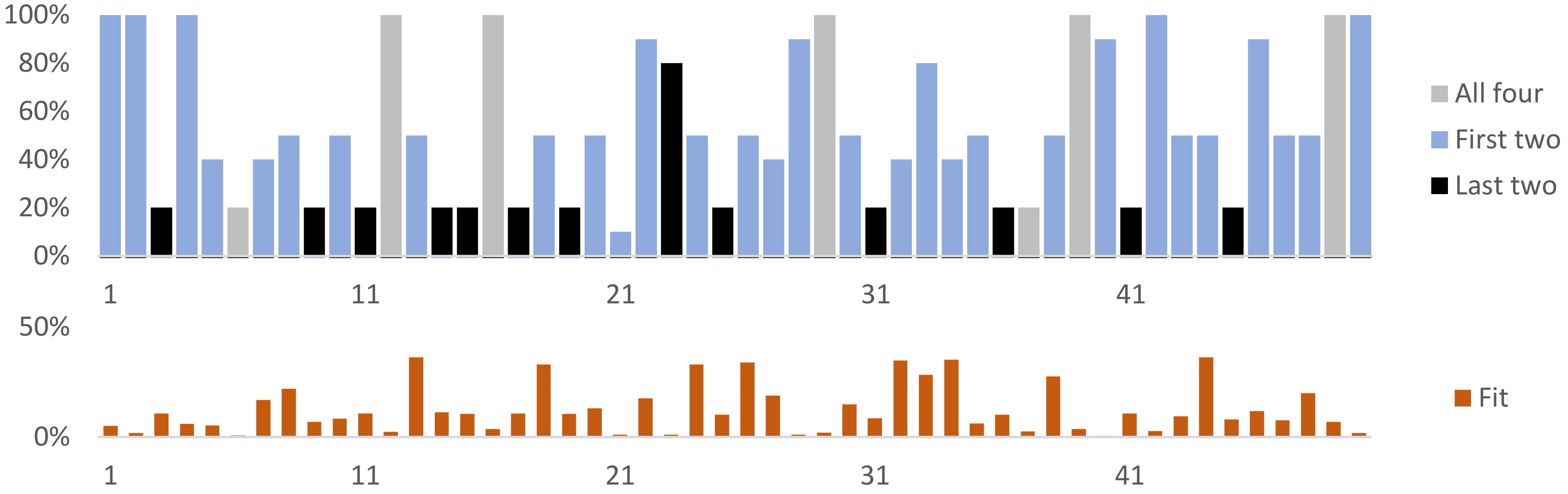
Procedure

- We simulate 500 observations as a training sample, and an additional 50 for testing (taking every tenth observation of a new simulated sample).
- For each prediction task from the testing sample, we compute the fit for relevance-based predictions based on different collections of variables (all four, the first two, and the last two) and different thresholds for observation relevance (increments of 0.1 from 0 to 0.9).
- We select the specification with the greatest fit and evaluate this prediction against the actual testing outcome.

Regime simulation: Results

- Out-of-sample outcomes are 89% correlated to CKT predictions (versus 54% for linear regression).
- Absolute errors are -43% correlated to relevance-based fits (versus -15% for linear regression).

Fraction of observations included (top) and fit (bottom)

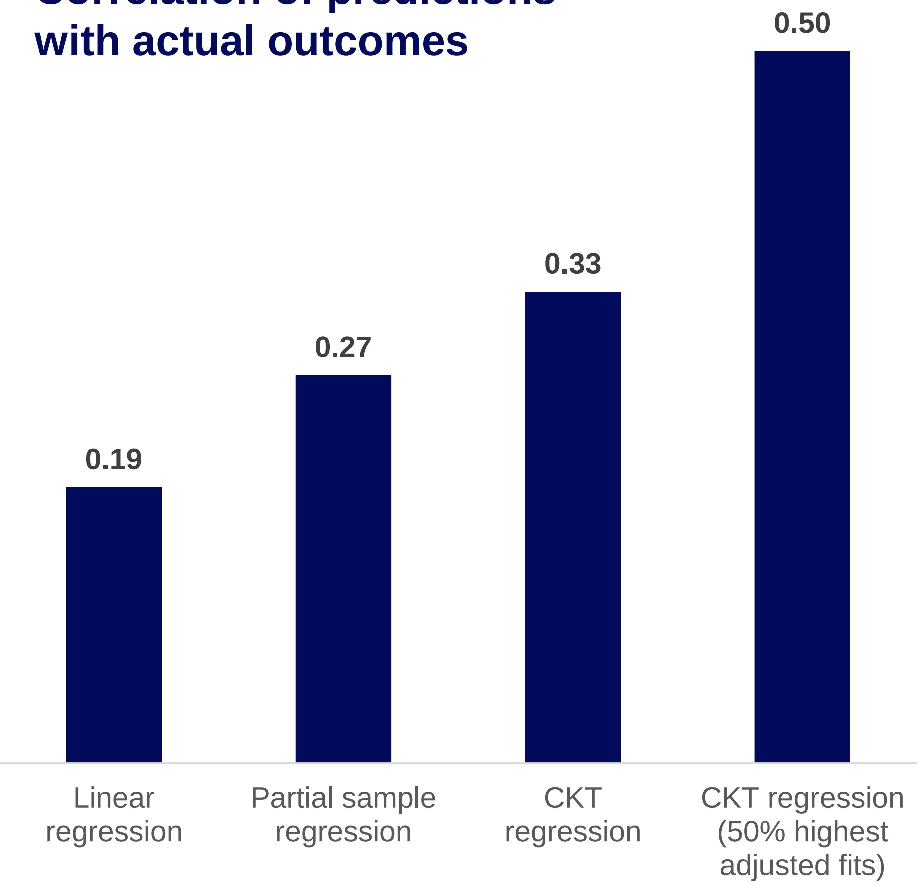


For illustration only. Source: State Street Global Markets.

Empirical application: Predicting NBA draft prospect performance

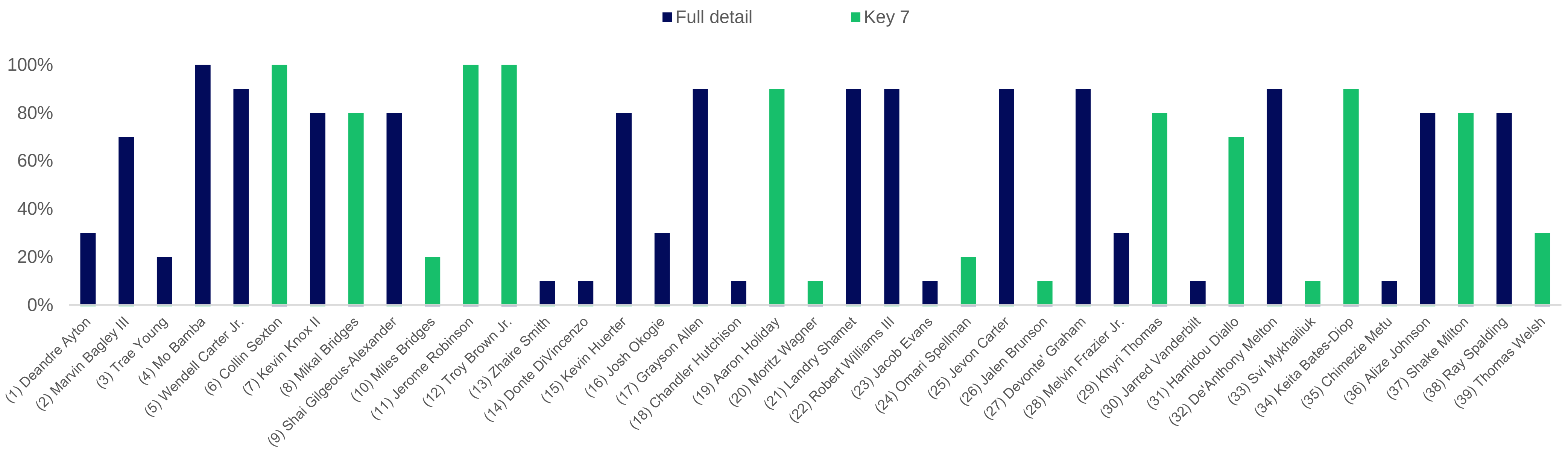
- Predict BPM (average box score plus/minus) for the 2018-2019 season for 39 rookie draft picks.
- Training sample: 249 previously drafted players from 2011 to 2017.
- Predictive variables: physical attributes (2), performance in final college season (10), college team success (2), draft team success (2).
- CKT regression, allowing relevance/similarity censoring, variable selection, and adjusted fit to reflect asymmetry and number of predictive variables.

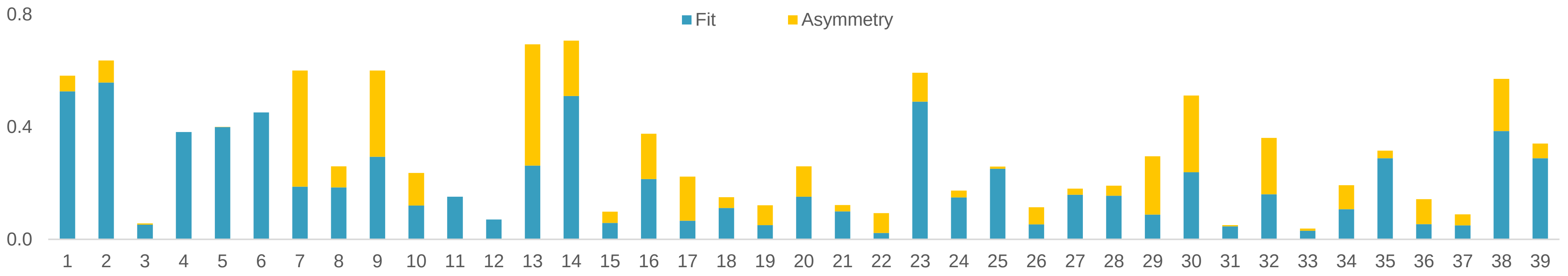
Correlation of predictions with actual outcomes



Source: "How to Predict the Future Performance of NBA Draft Prospects" by Czasonis, Kritzman, Kulasekaran and Turkington (Working paper, 2023).

Empirical application: Predicting NBA draft prospect performance





Source: "How to Predict the Future Performance of NBA Draft Prospects" by Czasonis, Kritzman, Kulasekaran and Turkington (Working paper, 2023).

Comparative summary

	Linear regression (LR)	Machine learning (ML)	Relevance-based prediction (RBP)
Transparency	⬜ Despite its simplicity, LR is silent about the impact of each observation and the quality of individual predictions.	🟥 The most powerful ML algorithms are notoriously opaque.	🟩 RBP shows how observations contribute to a prediction and quantifies confidence for each prediction task.
Adaptability	🟥 LR works well only for static linear relationships.	⬜ Despite their capacity to model complexity, ML models do not adapt their information use to new prediction circumstances.	🟩 RBP identifies the optimal sample of observations and variables simultaneously for each prediction task.
Non-arbitrariness	🟩 LR has a strong theoretical justification.	🟥 ML is guided by empirical efficacy rather than a core set of theoretical principles.	🟩 RBP is theoretically justified by both the Central Limit Theorem and information theory and is mathematically unified with linear regression.

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Disclaimers and Important Risk Information [2023.01]

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