One-Pass Ranking Models for Low-Latency Product Recommendations

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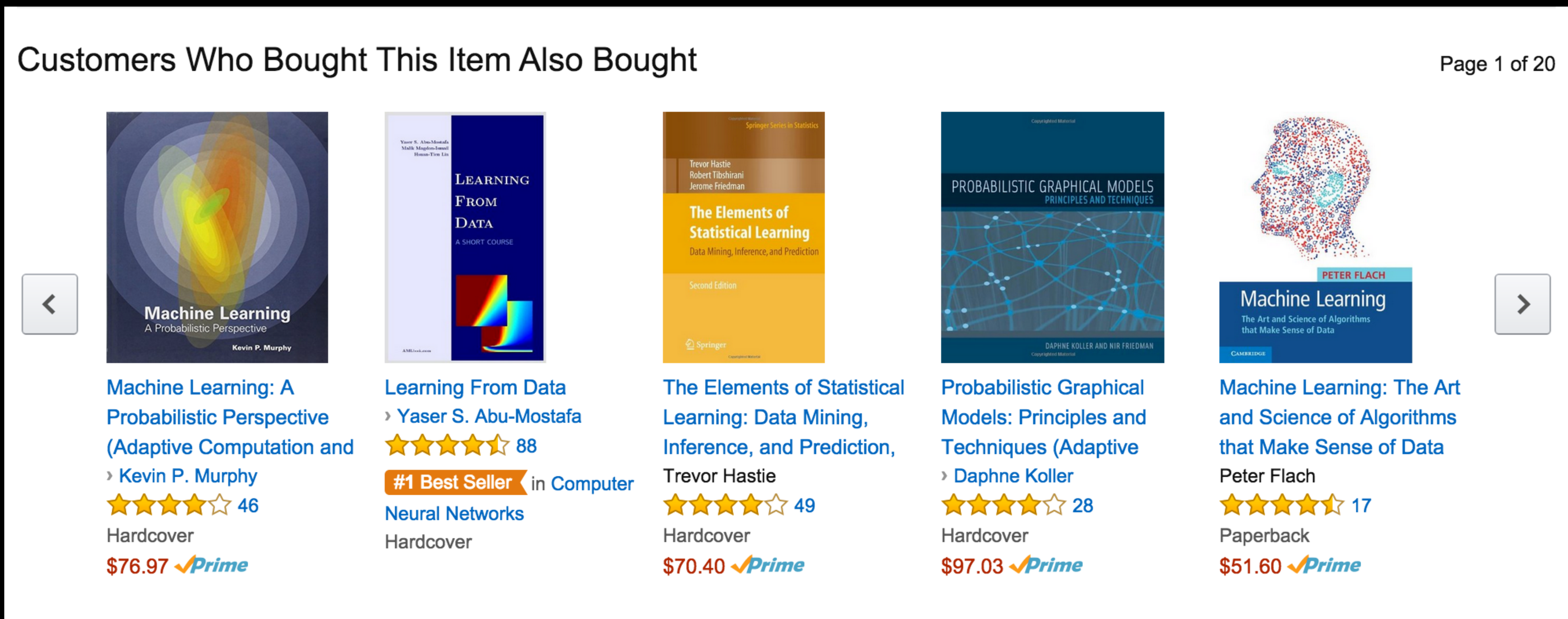
Product Recommendations



Product Recommendations

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   Large # of features

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   (<few ms)

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Our approach
Product Recommendations

Small memory footprint

Fast training time

Low prediction latency

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Low prediction latency

$\longmapsto$

Stochastic optimization

One pass learning

Our approach

Product Recommendations

Small memory footprint

Fast training time

$\longrightarrow$ Stochastic optimization

One pass learning

Low prediction latency $\longrightarrow$ Sparse models

Learning Ranking Functions

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Three broad families of models

1. Pointwise (Logistic regression)
2. Pairwise (RankSVM)
3. Listwise (ListNet)

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Loss functions

- Evaluation functions (NDCG)
- Surrogate functions

Loss Function

Lambda Rank (Burges et al., 2007)

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	Product 1	Product 2	Product 3	Product 4
$\mathbf{X}$: Features	$\mathbf{x_1}$	$\mathbf{x_2}$	$\mathbf{x_3}$	$\mathbf{x_4}$
$\mathbf{r}$: Ground-truth Rank	1	1	2	3

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Importance of sorting i and j correctly

$$\Delta\mathcal{M} = \mathcal{M}(\mathbf{r}) - \mathcal{M}(\mathbf{r}_{i/j})$$

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Loss

$$L(\mathbf{X}; \mathbf{w}) = \sum_{\mathbf{r}_i \leq \mathbf{r}_j} \Delta\mathcal{M} \cdot \Delta S$$

ElasticRank

Introducing Sparsity

Adding l_1 and l_2 penalties

$$L^*(\mathbf{X}, \mathbf{w}) = L(\mathbf{X}, \mathbf{w}) + \lambda_1 ||\mathbf{w}||_1 + \frac{1}{2}\lambda_2 ||\mathbf{w}||_2^2$$

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Both λ_1 and λ_2 control model complexity

- λ_1 trades-off sparsity and performance
- λ_2 adds strong convexity & improves convergence

Optimization Algorithms

Extensions of Stochastic Gradient Descent

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pSGD Pruned Stochastic Gradient Descent

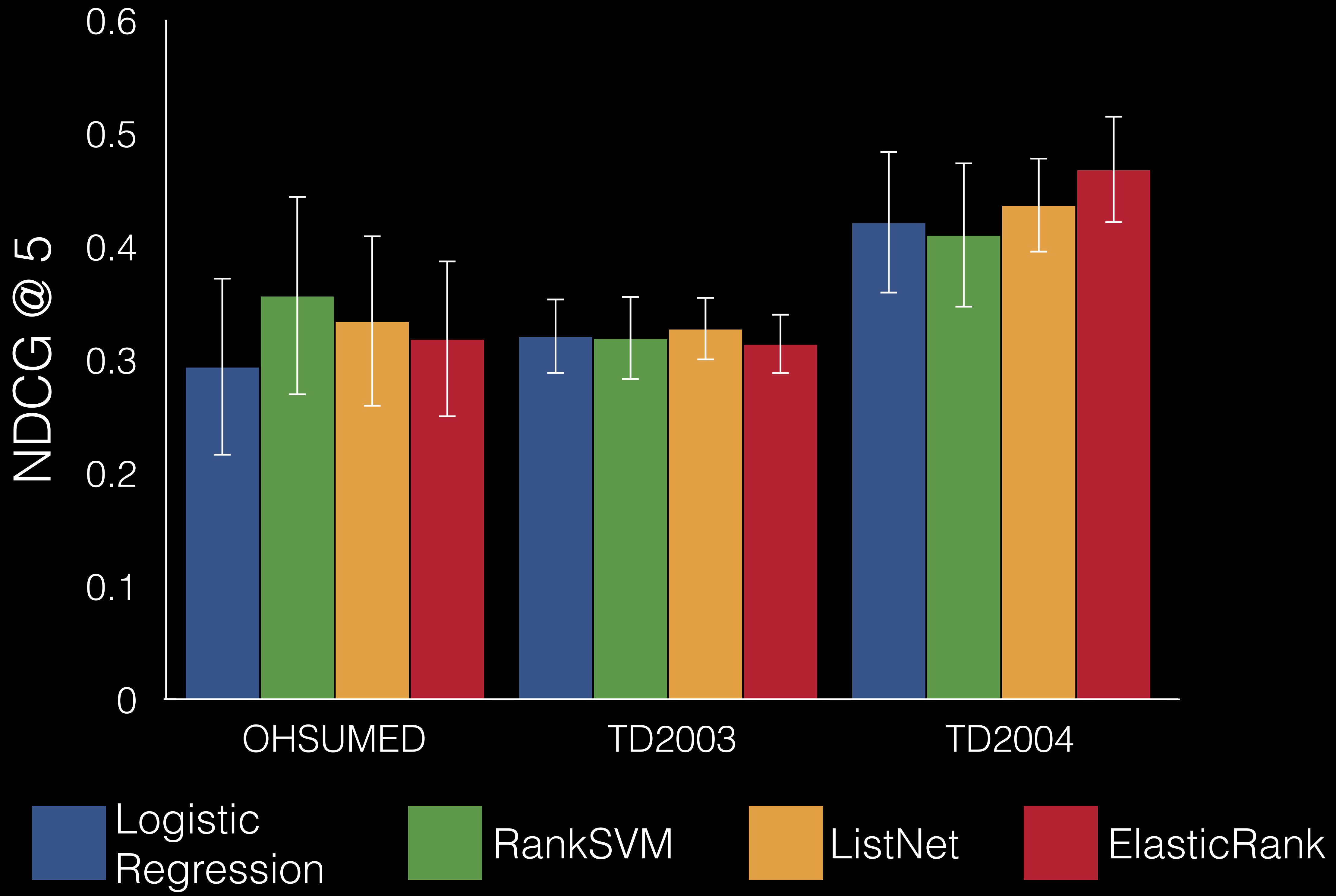
- Prunes every k gradient steps
- If $|w_i| < \theta \Rightarrow w_i = 0$

Hyper-parameter Optimization

- **Turn-key** inference
- Automatic adjustment of hyper-parameters
- Bayesian Approach (Snoek, Larochelle, Adams; 2012)
  - Gaussian Process
  - Thomson Sampling

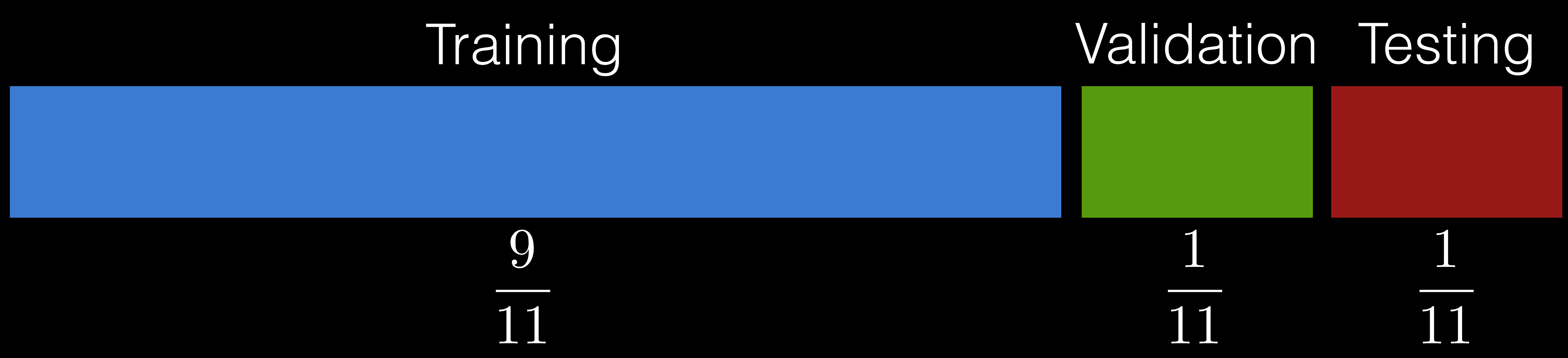
LETOR Experiments

ElasticRank is comparable with state-of-the-art models



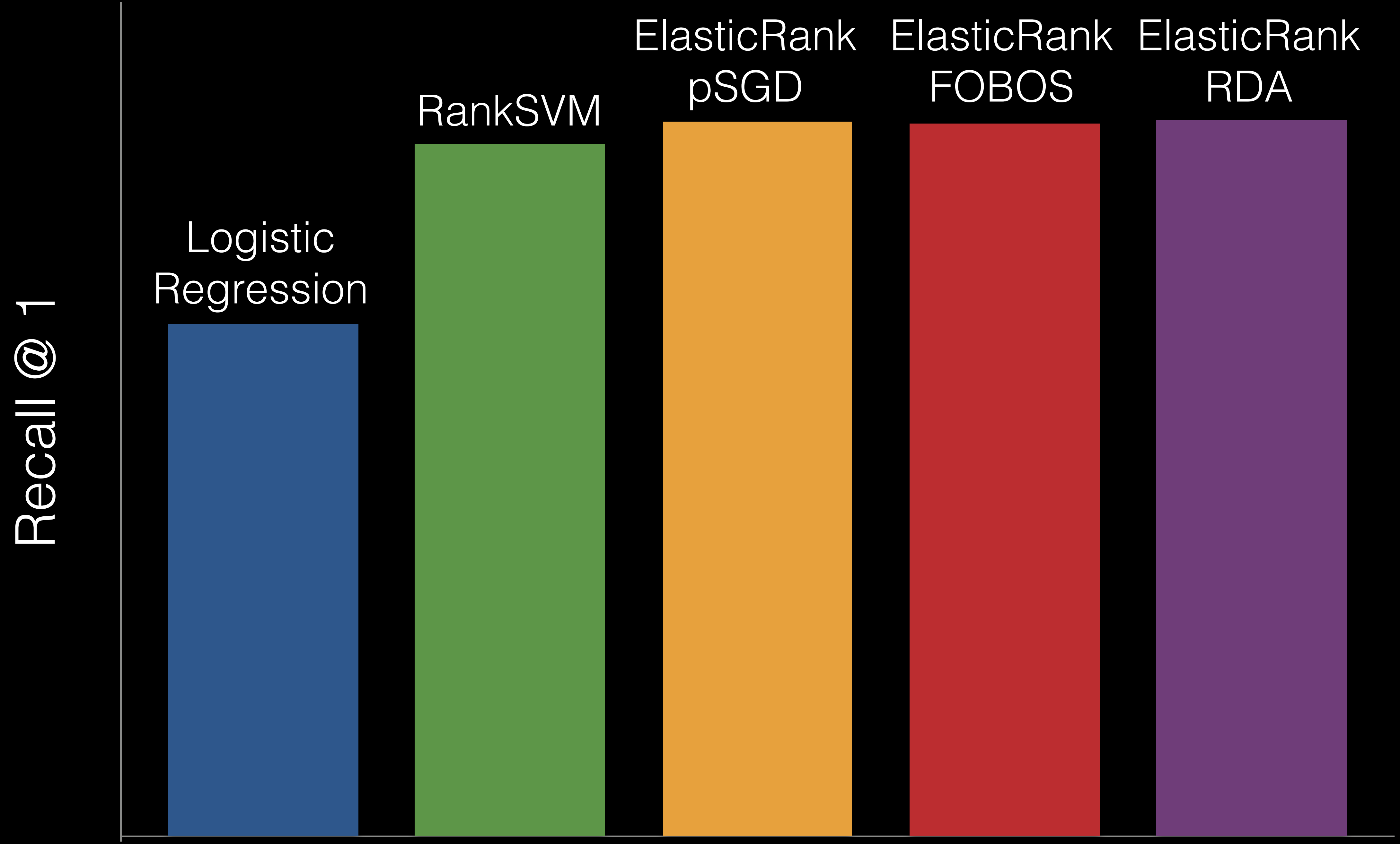
Amazon.com Experiments
Experimental Setup

- # examples ≈ millions
- # features ≈ thousands (millions of dimensions)
- Purchase logs from contiguous time interval



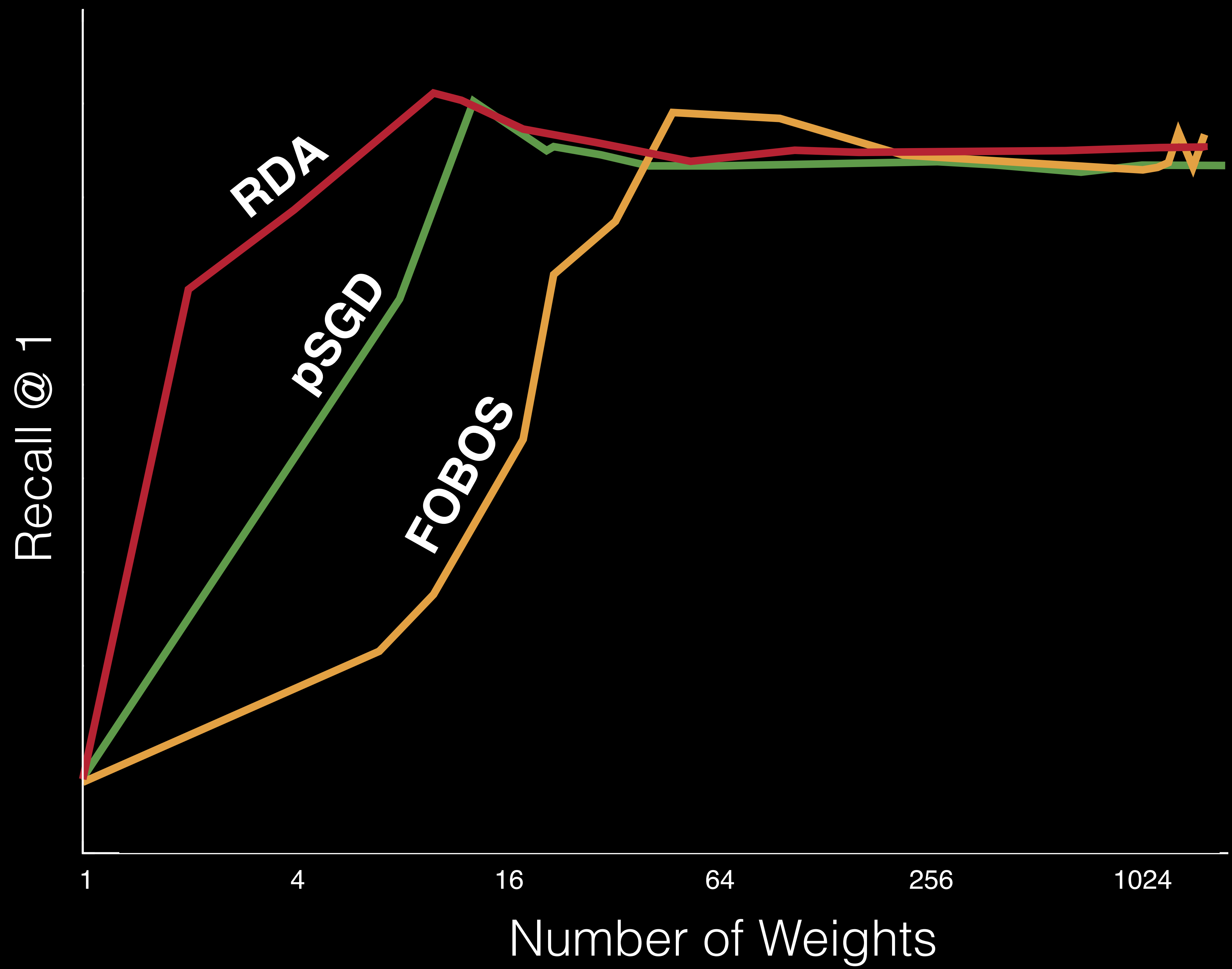
Experimental Results

ElasticRank performs best

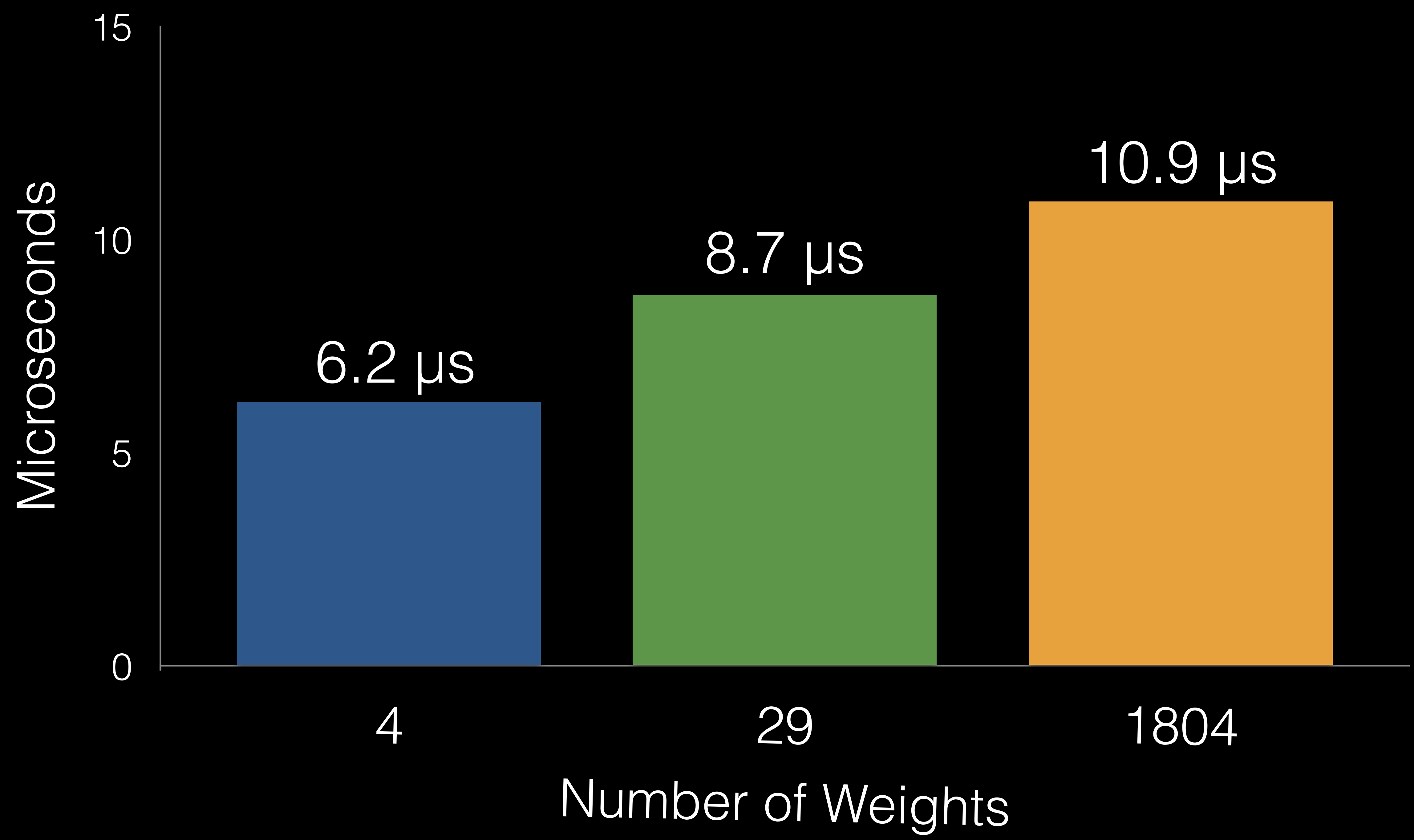


Sparsity vs Performance

RDA achieves the best trade-off



Prediction Time



Contributions

How to learn ranking functions with

- Single pass
- Small memory footprint
- Sparse

WITHOUT sacrificing performance

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