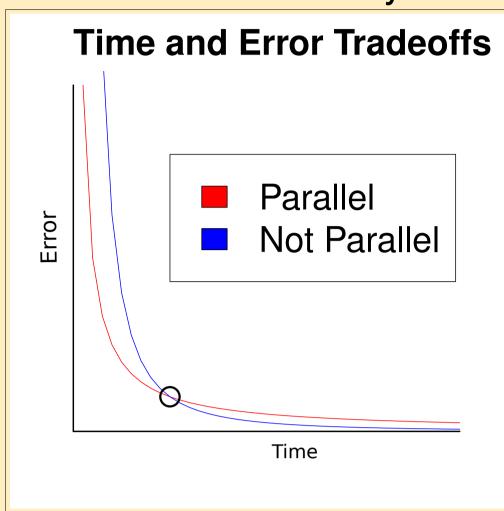
# An Optimization Layer for Distributed Matrix Computations

Jonah Brown Cohen, Tselil Schramm, and Ben Weitz

### Motivation

- ▶ Big data companies like Facebook, Netlix, or Google perform large-scale distributed matrix computations
- Computations experience trade-offs in accuracy vs. time or money.



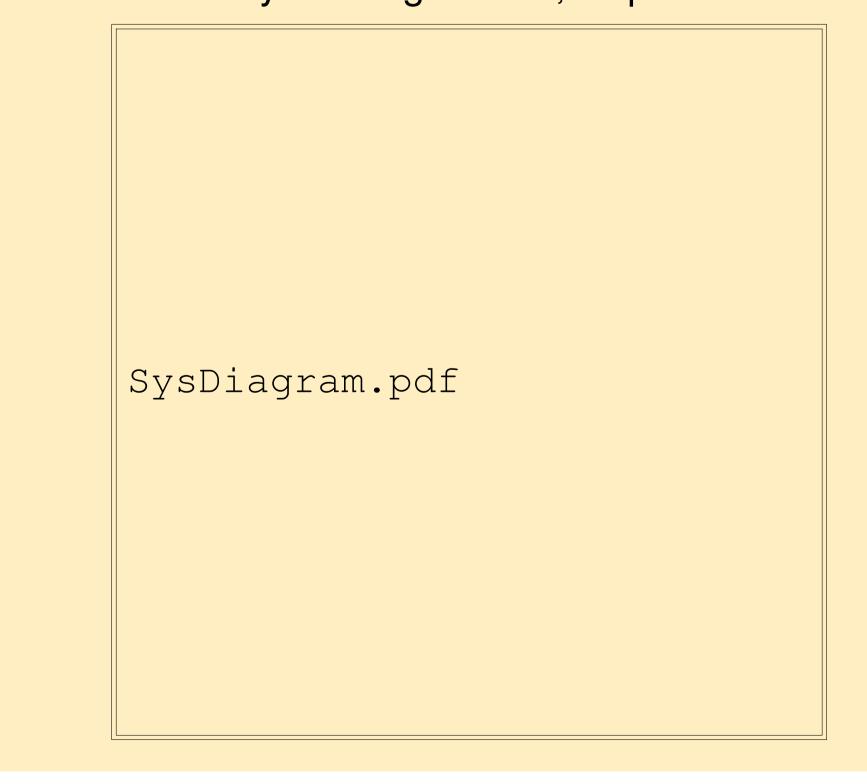
- Human operators manually tweak parameters and partitioning
   Humans are prone to error and costly to hire!
- ► Solution: Build an optimization layer to automatically tweak and manage these computations
- Learn to adjust parameters from past computations
   Incoming jobs come with budgets of time or accuracy that must be met

# Objective

Create an optimizer that automatically picks algorithm parameters and the degree of data partitioning to meet budget specifications

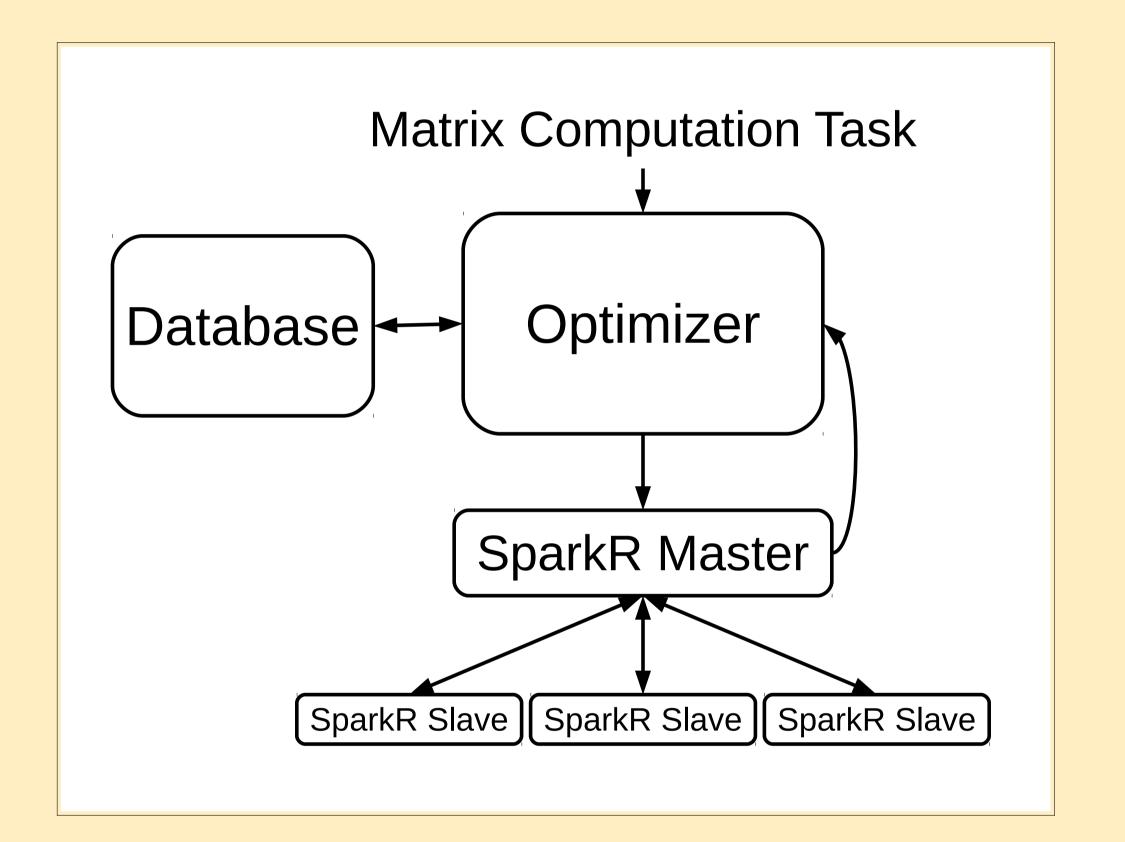
### Framework

- Optimizer built on Python
- ▶ Interfaces with matrix algorithms implemented in SparkR or MLBase
- Optimizer interfaces directly with algorithms, all parameters hidden from user



### Optimizer Design

- Architecture-independent
- Chooses parameters based on statistics from prior jobs ▶ sdflksad
- Adaptive
- Stores statistics from previous jobs on instances with similar distribution, and improves predictions with time.
- Local-optimum Avoiding
- ▶ In "explore mode" we choose the instance parameters randomly, according to a distribution specified by the
- ▶ sdf



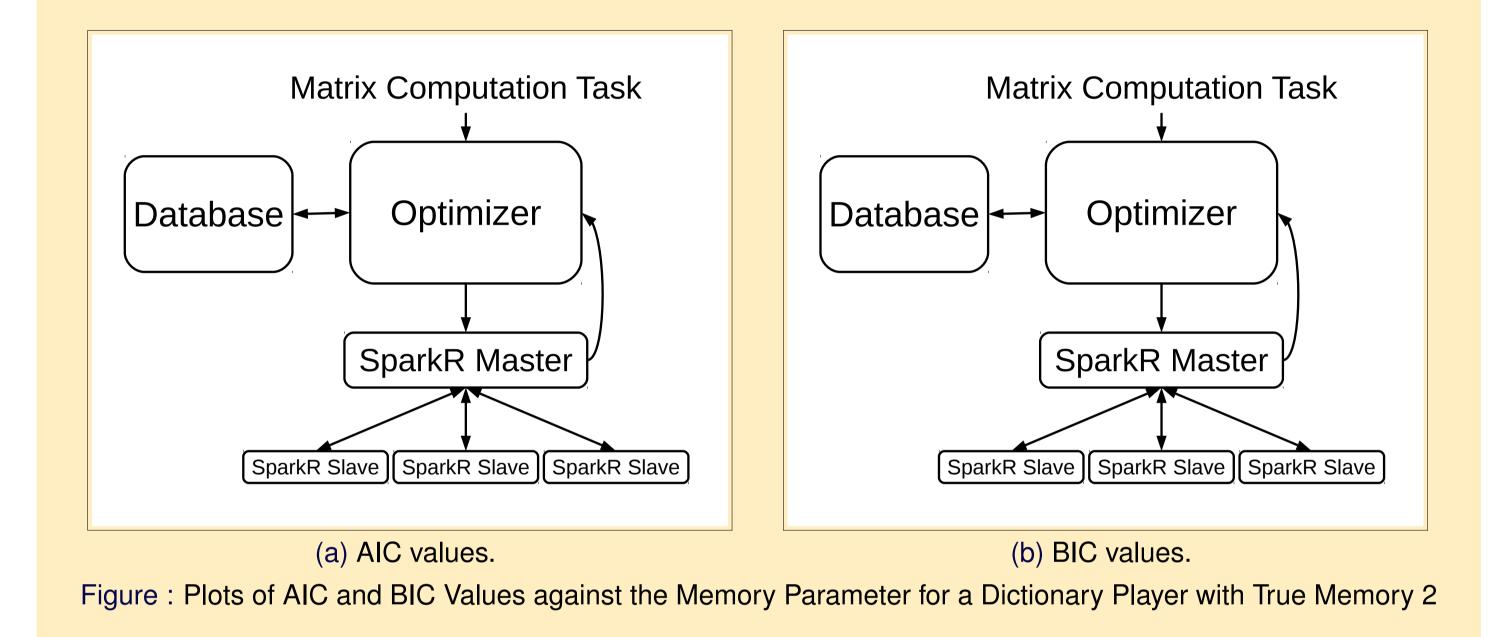
## Implementation

- ► The words chosen by the adversary are hard,
- But once you know theyre difficult it's easy to adjust.
- ► Top 12 words (probability of losing in 6 turns):

### Evaluation

#### Can the Al determine the correct memory of a player?

- Generated data for players with restricted memory.
- Extremely large number of samples required for AIC.
  Can only implement model with memory parameters 1 through 3.
- Computed (corrected) AIC and BIC values
- AIC consistently overestimates.
- BIC consistently underestimates.
- Failure of AIC due to information available to player not captured by the model.



# Future Work

#### Achievements:

- Can learn a player's strategy assuming restricted memory.
- Can choose words that are hard for that player.
- Compiled a list of hard words for a dictionary-using frequency player. Also hard for regular humans.

#### Future Work:

- Online Learning.
- Foiling an Adaptive Player.
- Can we learn an adaptive strategy quickly and counter it?
- ▶ Is there a Nash Equilibrium to the responses?

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