Reinforcement Learning for Automated Performance Tuning: Initial Evaluation for Sparse Matrix Format Selection

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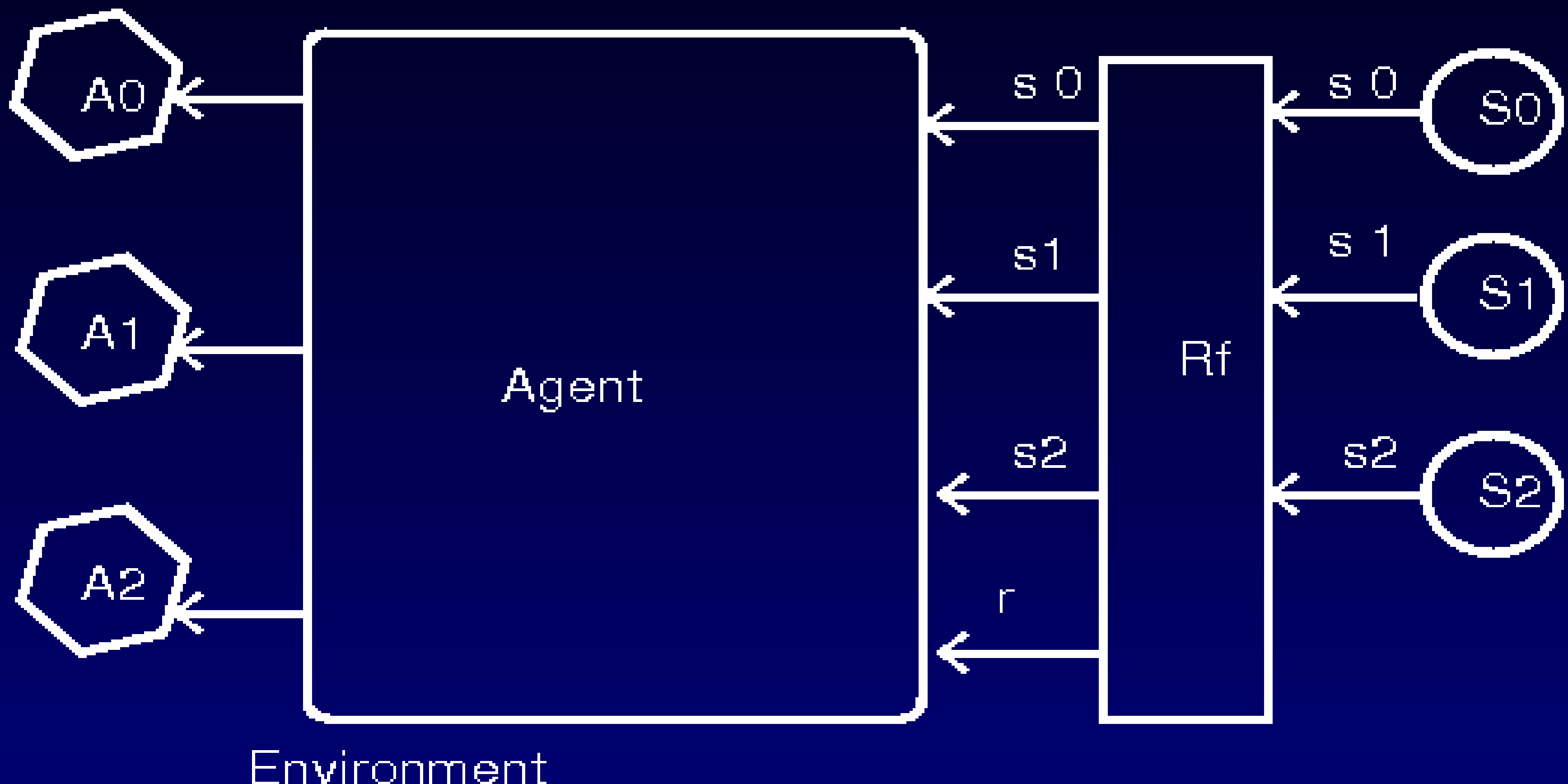
Outline

- Background on Reinforcement Learning
- Motivation
- General framework and sample problem
- Evaluation

What is Reinforcement Learning

- Learning how to act based on experience
  - Dynamic and probabilistic environments.



- Contrast to supervised learning: no examples required.

Automated Tuning as a Reinforcement Learning Problem

- Automated Tuning
  - Often requires search – exhaustive or heuristic
  - Rapidly changing conditions require many searches
- Reinforcement Learning
  - No need for heuristic: just define the goal.
  - Rather than search for an optimal solution, RL searches for an optimal mapping from states to optimal solutions
  - Our idea: Rate of change of mappings is less than rate of change of solutions.

General Framework
and
Sample Problem

Sample problem: Sparse Matrix Format Selection

- A *sparse* matrix is a matrix with zeroes which can be profitably ignored.
- There exist many different storage formats for achieving this.
  - Format efficiency varies with matrix structure
  - This is generally only knowable at runtime
- Our goal: Given a matrix:
  - Characterise it
  - Select a format for it
  - Reformat the matrix and multiply it by a vector

Existing Tuning Methods

- ATLAS, PhiPAC
  - Tune based on architecture – for dense matrices
- OSKI / AcCELS
  - Architectural tuning defines a search space
  - Format selection based on (heuristic) runtime search of this space

Applying Reinforcement Learning

- Actions
  - Switching to different configurations
  - *CSR, BCSR-8x8, COORD*
- Sensory perceptions
  - N sensors map onto an m-dimensional state space
  - *Rows, Columns, Nonzeroes, Inter-row spread, neighbour count.*
- Reward
  - Any measurable quantity
  - *Inverse of execution time*

Selecting an Action

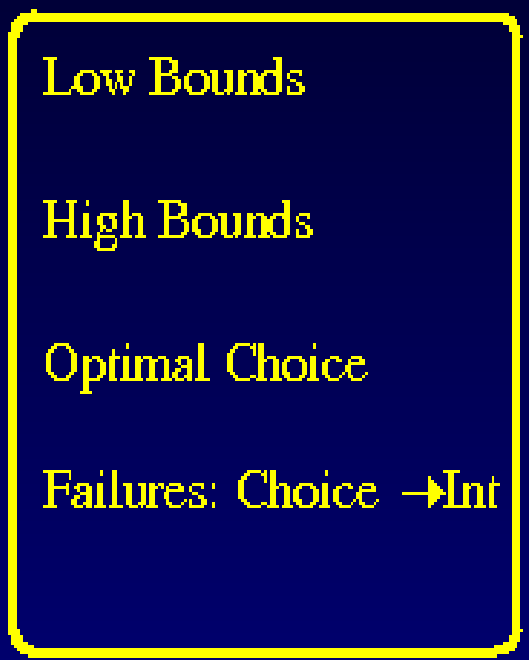
- Two types of action: Exploitation and Exploration
- Exploration costs, so only do it when it is likely to succeed.
- Exploration Chance: P = E + K, where
  - E is fixed at runtime
  - K varies based on the recent exploration success rate.
- Every time a choice must be made, exploration occurs with probability P.

The Mechanics of Exploration

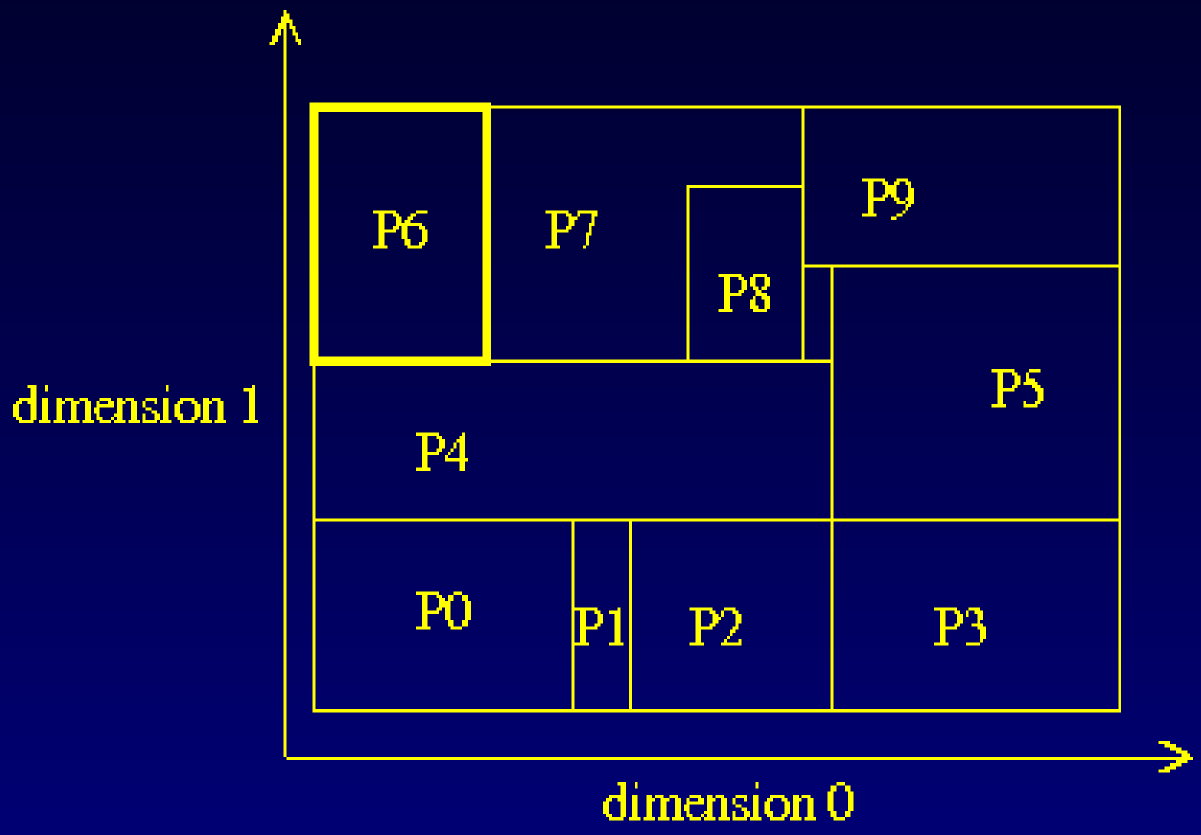
- Goal: Compare choices.
  - Assumption: a state persists for D steps, where D is a user-specified constant.
  - *In the sample problem, D is the number of multiplications*
- Break into multiple actions:
  1) Execute D/2 steps with the current optimal choice to obtain reward Rc
  2) Execute D/2 steps with an alternative choice to obtain reward Ra
- If Ra is better than Rc then exploration suceeded.

Representing the State Space

- The state space is discretised into partitions
  - Example with m = 2:

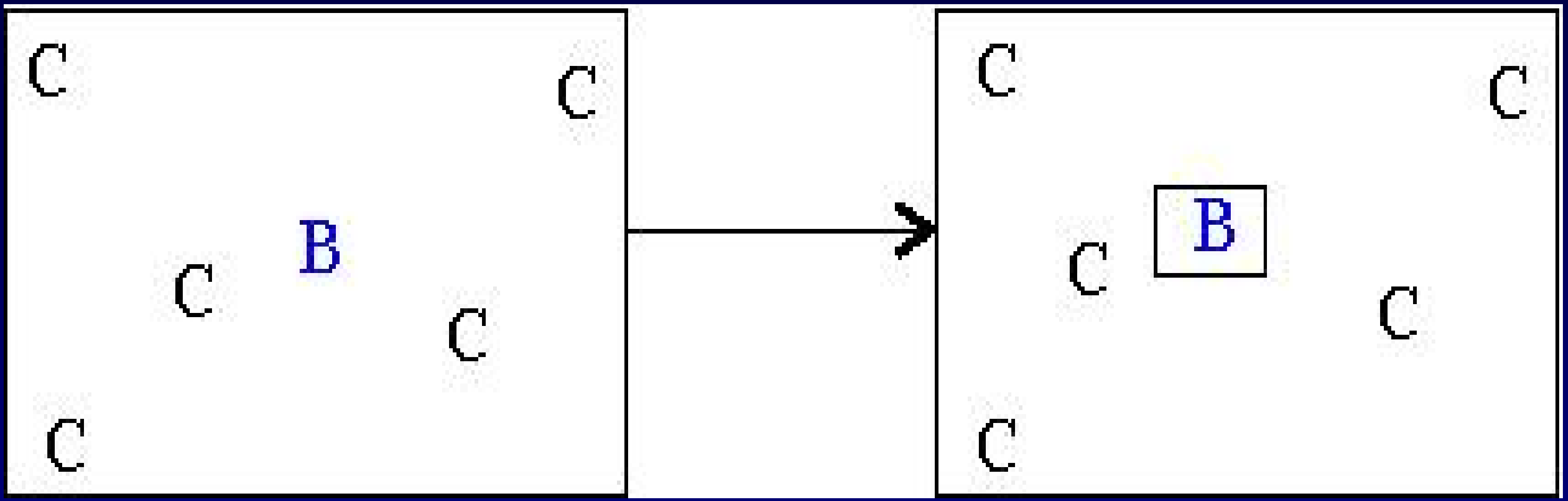


Partition P6



Using the State Space Representation

- Initial state:
  - One partition, no recorded failures, arbitary optimal choice
- Change results from exploration:
  - Failed exploration is remembered
  - Successful exploration results in a new partition:



- Partition width determines generalisation

Evaluation: Does the learning algorithm make good choices?

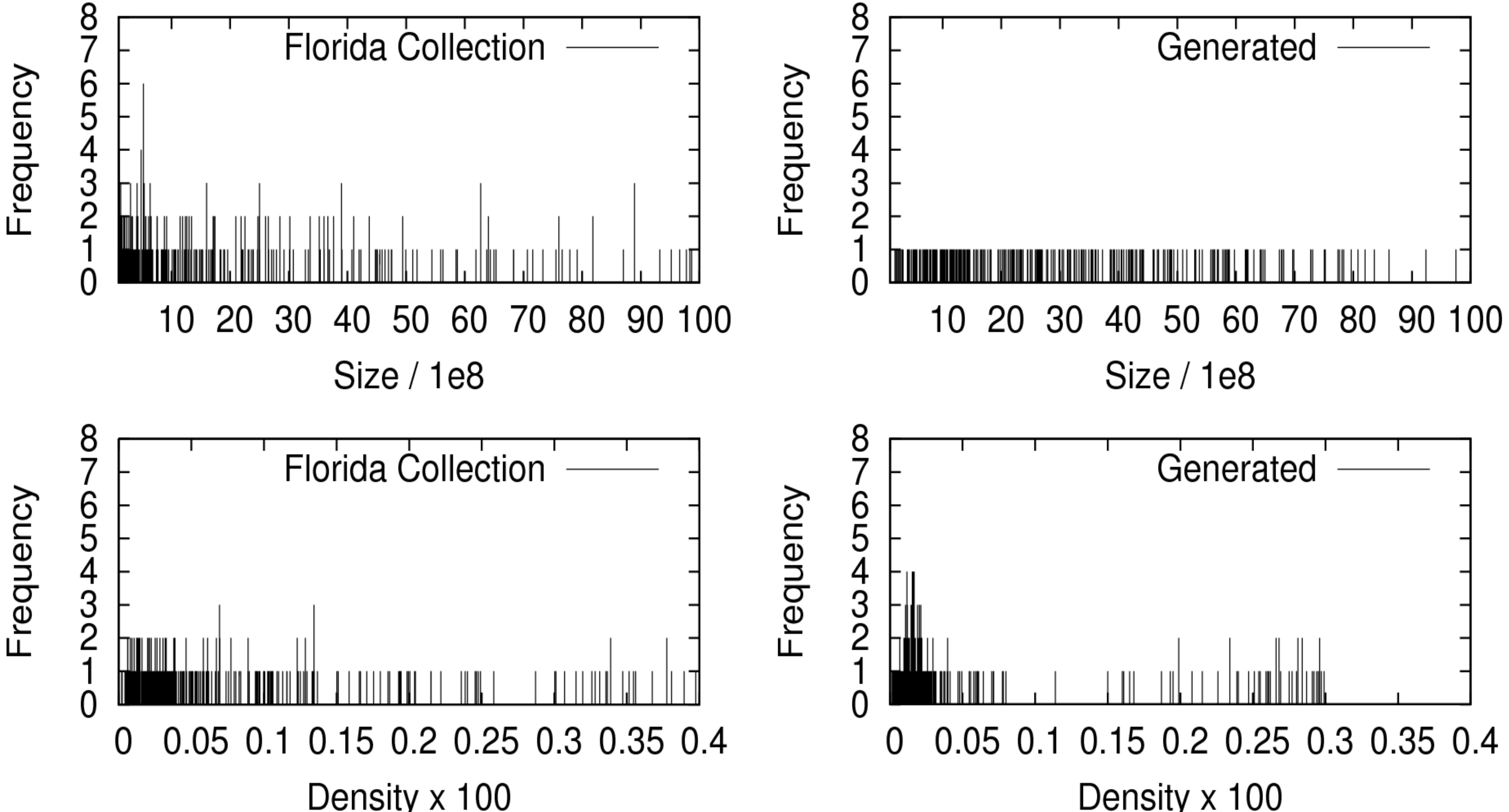
Evaluation Strategy

- Matrix generation
- Matrix sequence characterisation
- Defining an evaluation metric
- Simulation

Matrix Generation

- Large numbers of matrices needed.
- Generation through probabilistic selection of attributes
  - size, density, pattern
  - Via uniform and normal distributions.
- How realistic are the generated matrices?

Matrix Generation



- Not identical, but reasonably similar

Matrix sequence characterisation

- Characteristics of each matrix
- Time to change each matrix into each format
- Multiplication time for each matrix in each format.

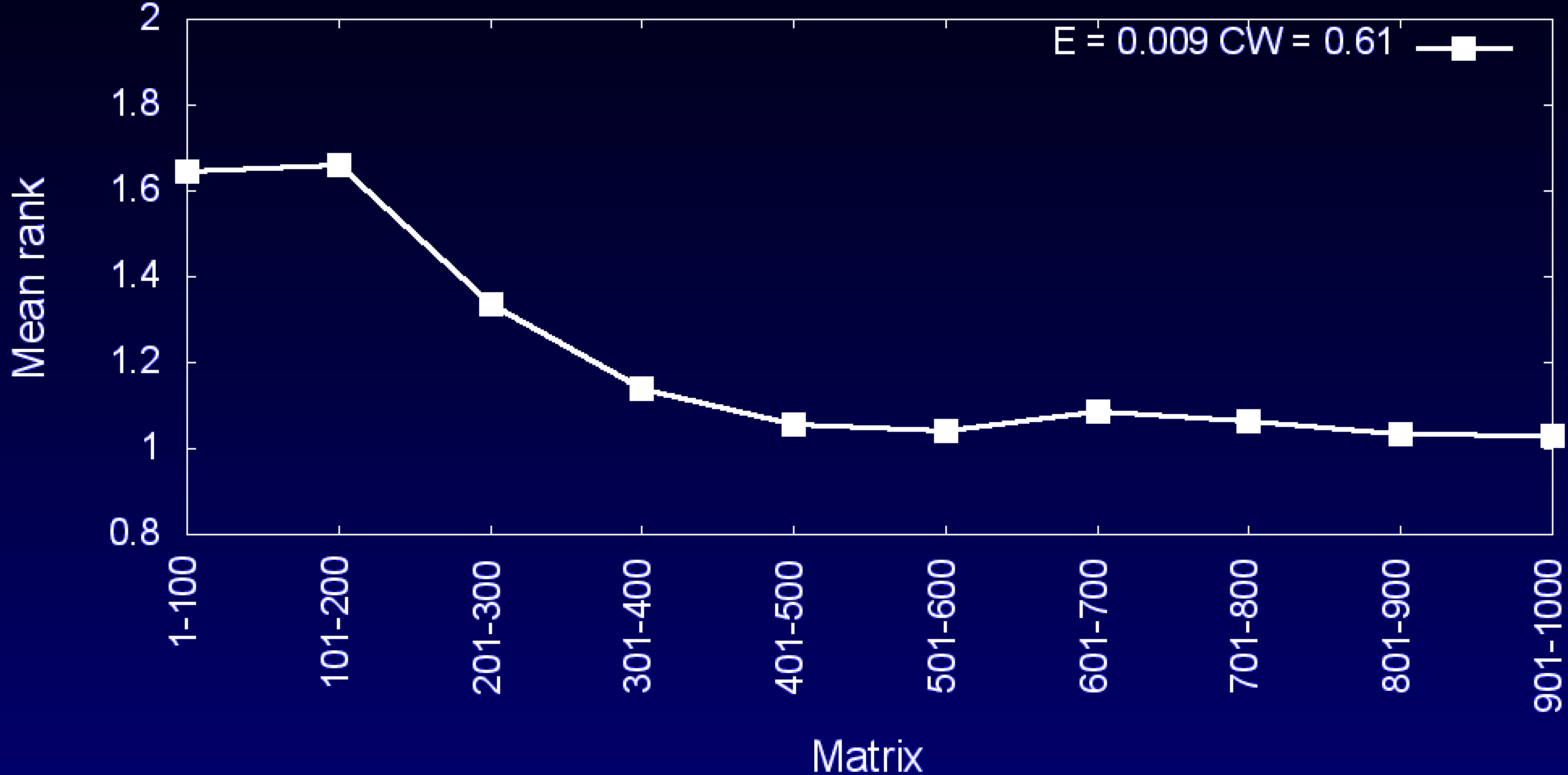
Defining an Evaluation Metric

- For each format F and each matrix m, define rank(F, m) = 1 if the format is optimal,
  3 if the format is the worst choice,
  2 otherwise
- Slice the matrix stream into windows of 100 matrices.
- For each window W, compute the mean rank achieved by the agent's choices

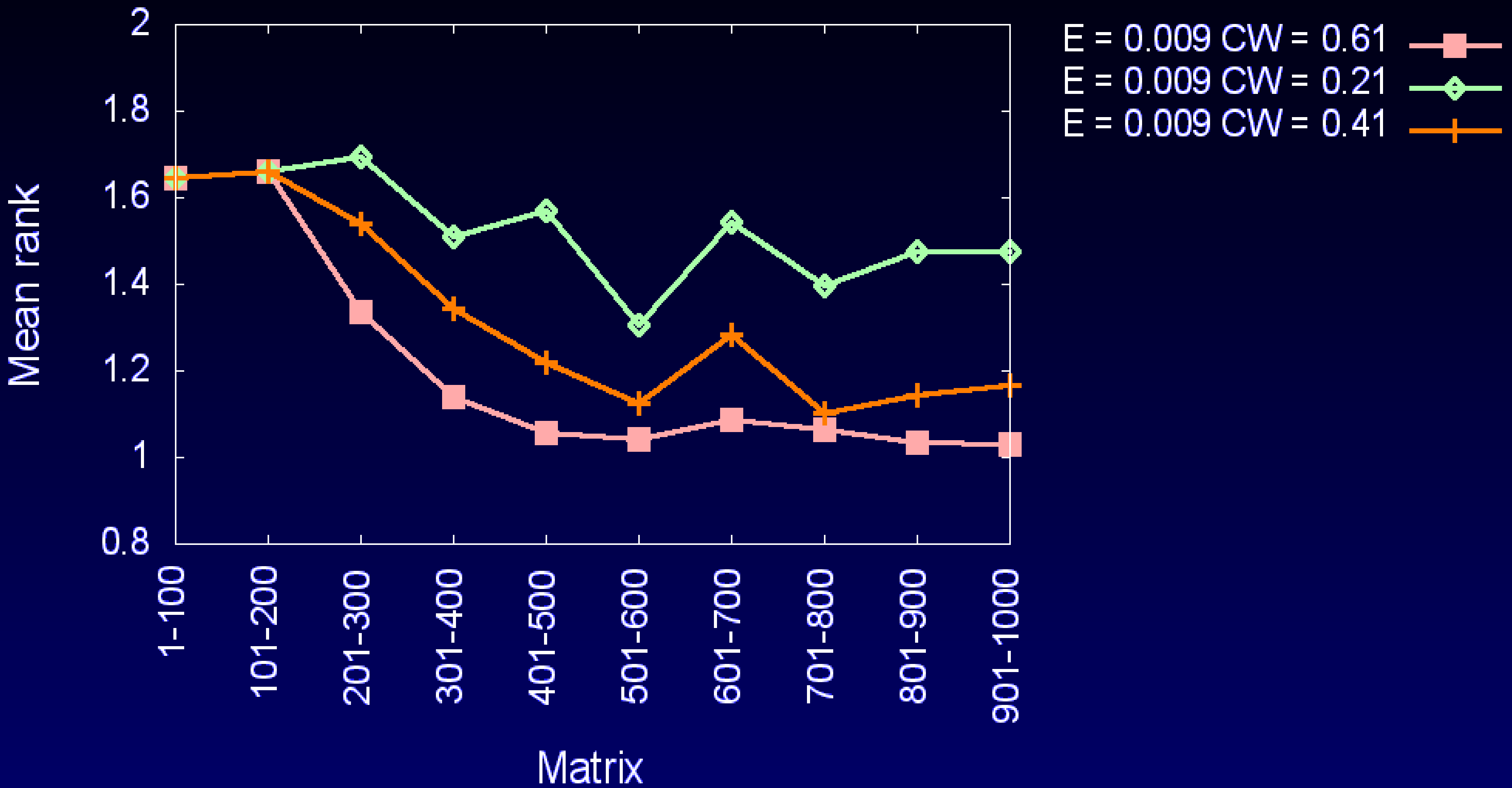
Results

- The algorithm made the correct choices
- The performance of the algorithm depends on its ability to generalise
- Generalisation reduces exploration.

The algorithm made correct choices

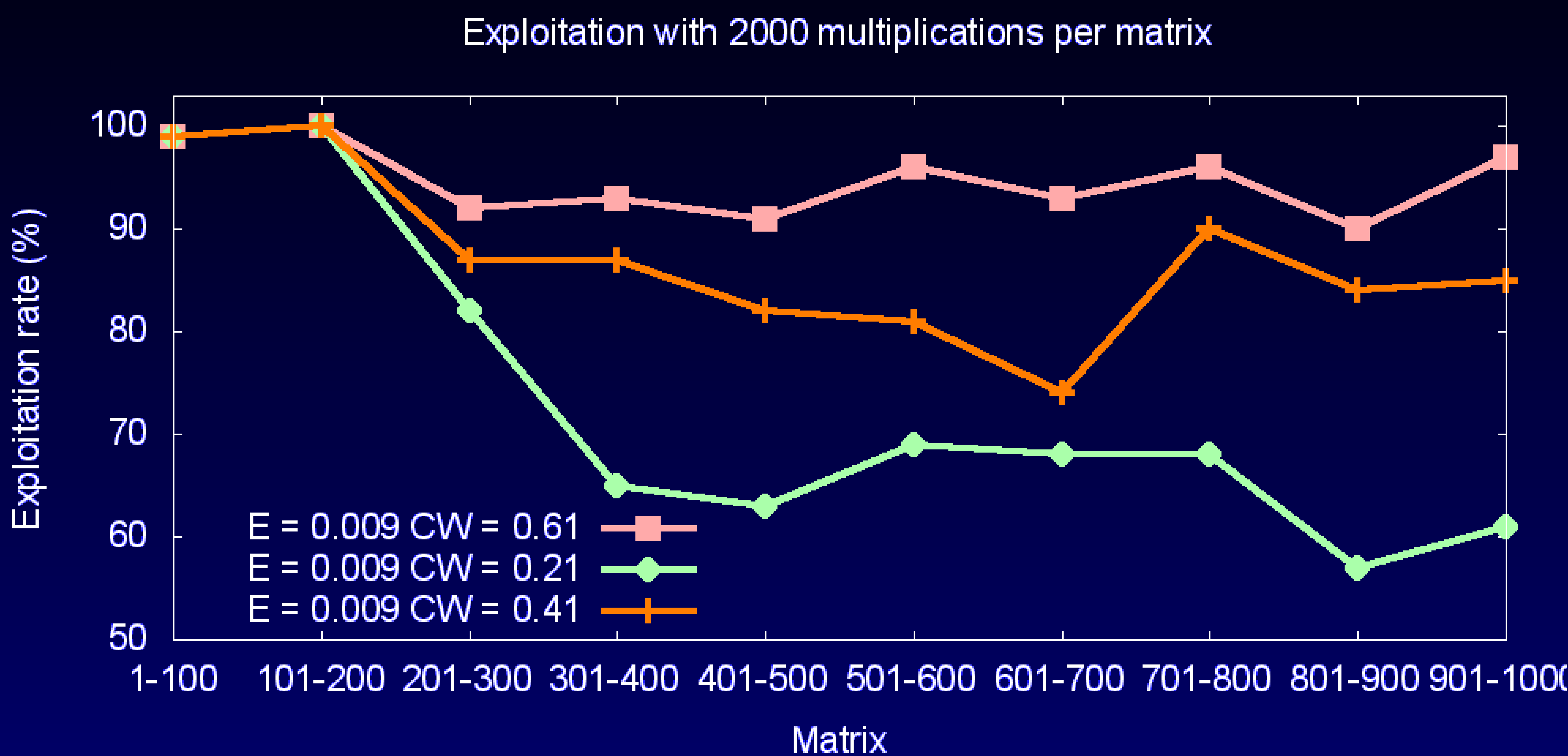


Parameter Sensitivity



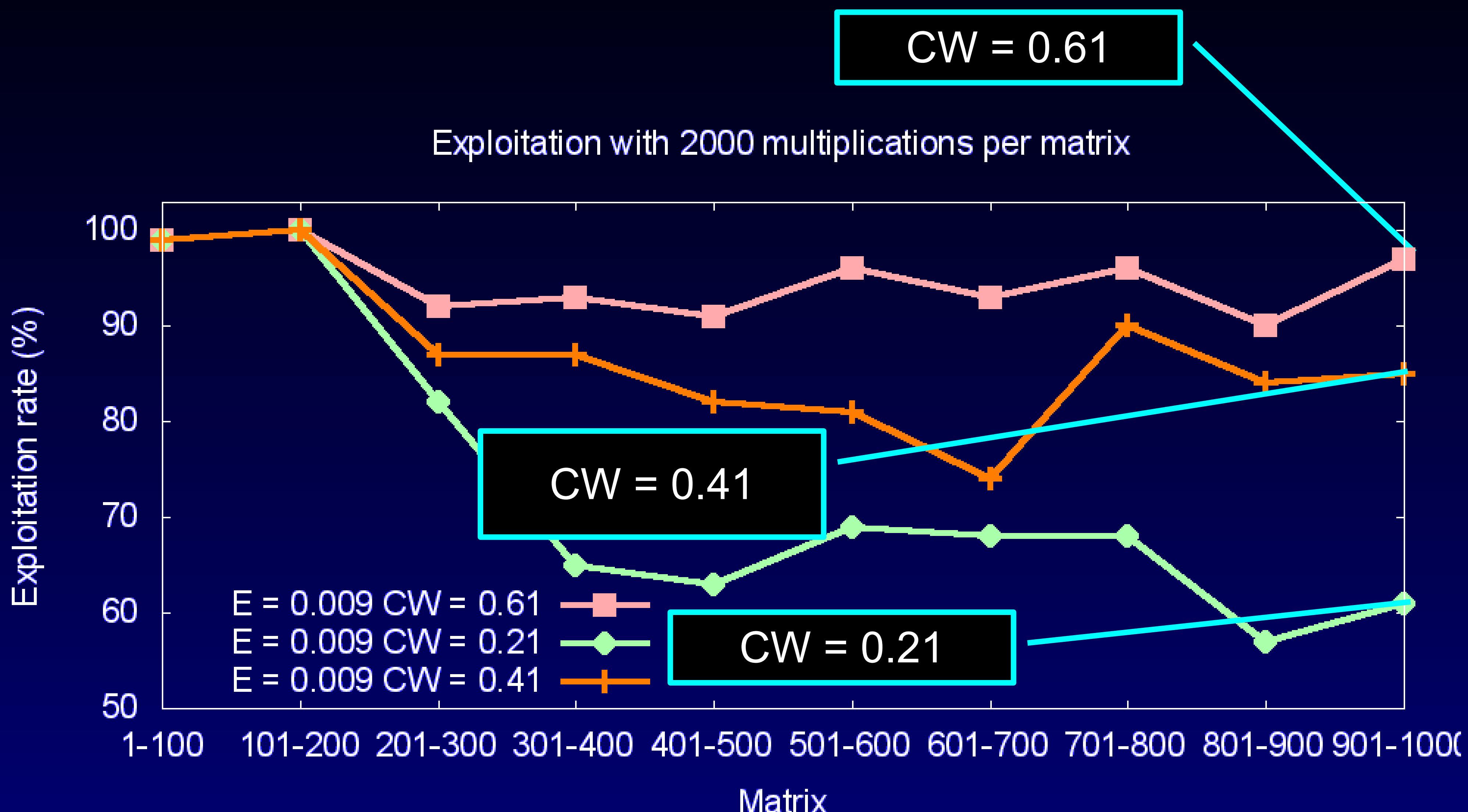
E = fixed exploration rate, CW = new partition proportion

Generalisation and Exploration



E = epsilon_base, CW = cut_width

Generalisation and Exploration



Best performance with least exploration: generalisation is important.

Discussion

- Execution time gains
- Place matrix generation on a sounder footing
- Models of matrix evolution
- Possible overfitting
- Tuning the learning algorithm

Questions?