A BRIEF REVIEW OF HYPERPARAMETER OPTIMIZATION METHODS FOR MACHINE LEARNING

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OUTLINE

1. Introduction
2. Methods
3. Results
4. Discussion
5. Conclusion
6. References

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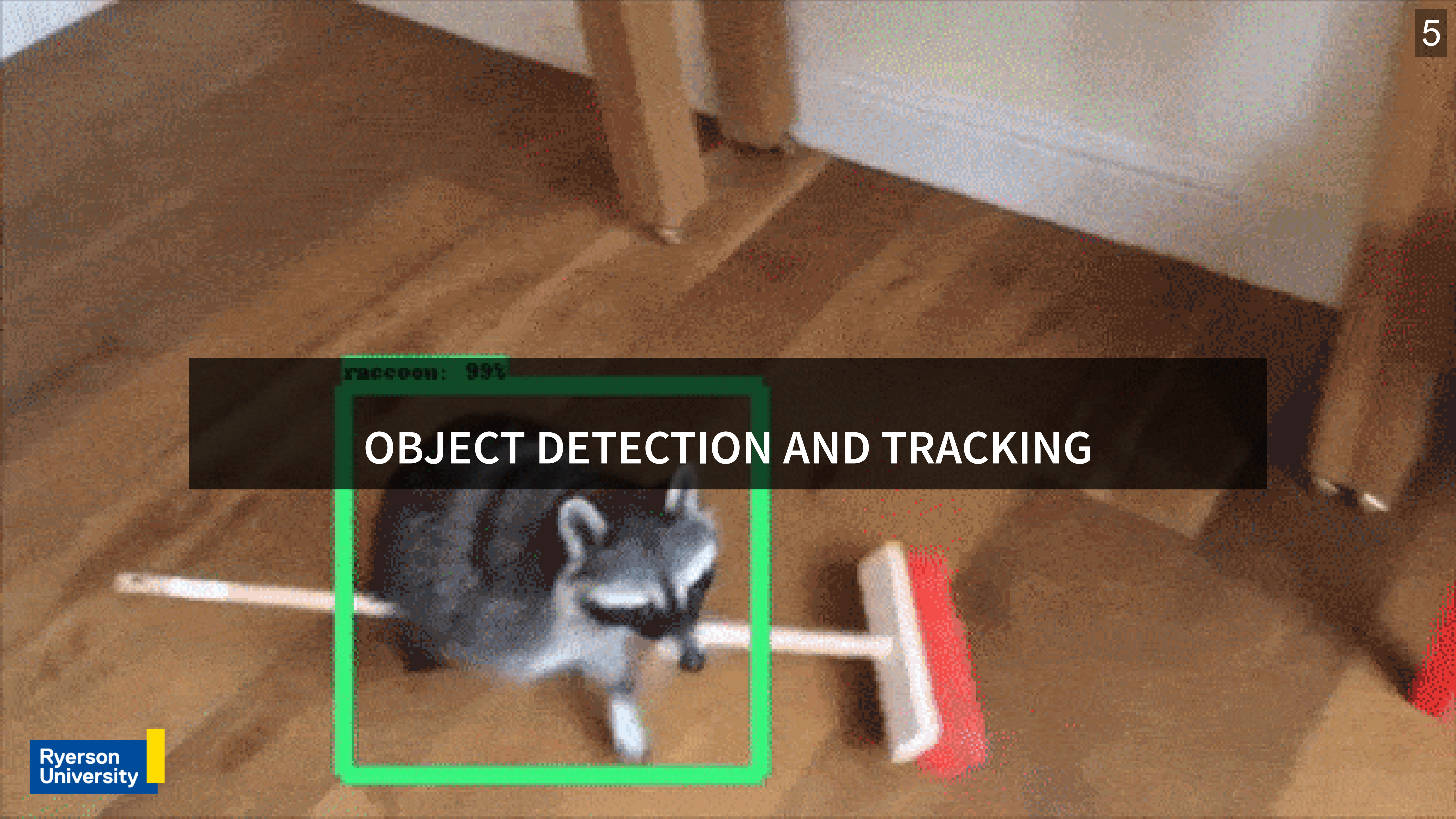
INTRODUCTION

MACHINE LEARNING

- Learn from data
- Accuracies > 99% possible
- Real-world applications

OBJECT DETECTION AND TRACKING



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MEDICAL IMAGE DIAGNOSES


Hurricane Harvey Flooding
Simonton, Texas
November 20, 2016 (Left)
August 30, 2017 (Right)
DISASTER MAPPING
DigitalGlobe
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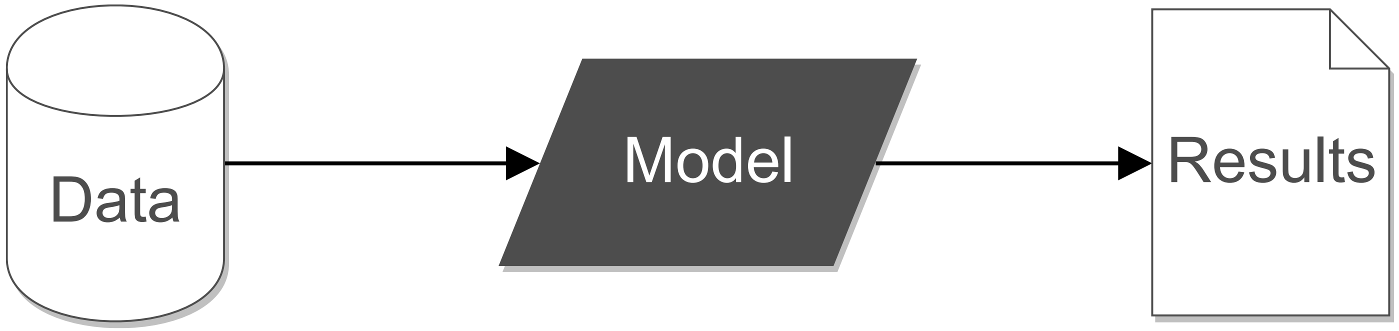
MACHINE LEARNING PROCESS



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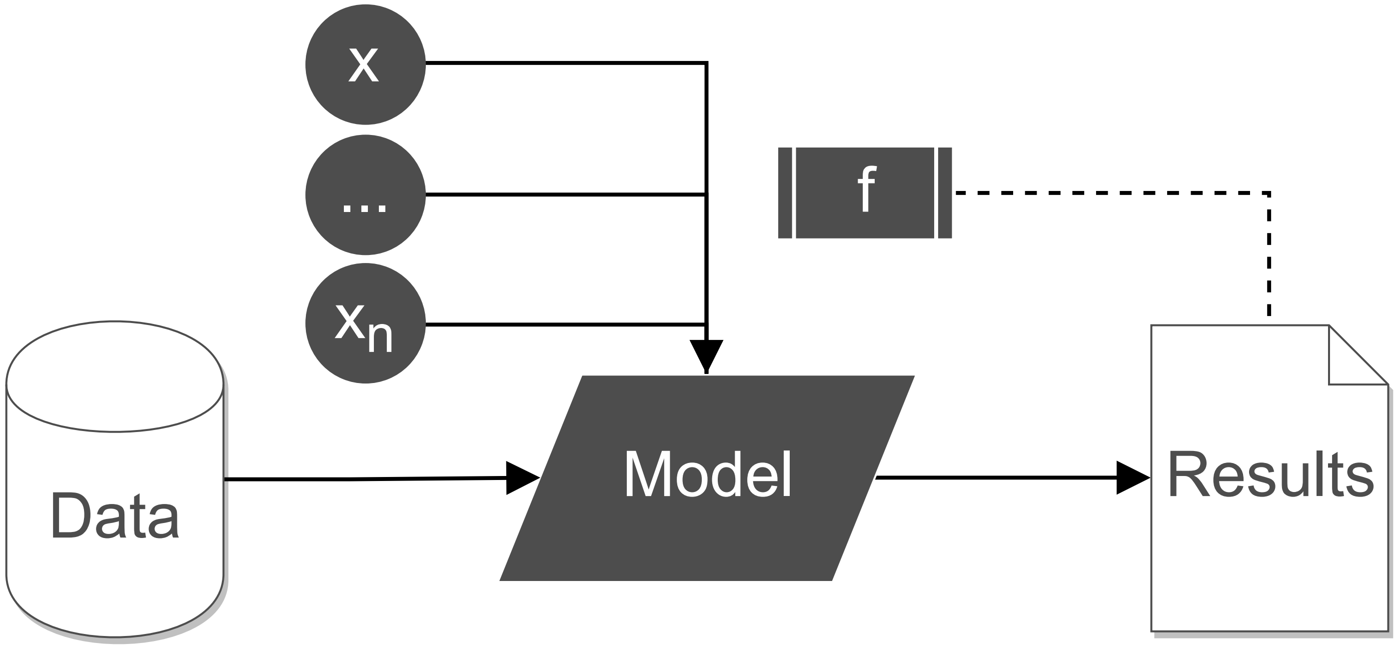
MACHINE LEARNING MODEL



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HYPERPARAMETERS

- Adjustable values
- Affect learning performance
- Before learning process

HYPERPARAMETER OPTIMIZATION

- Adjustable values $x \ldots x_n$
- Affect performance measure f
- Find optimal $x \ldots x_n$

$$\underset{x \ldots x_n}{\operatorname{argmax}} f(x \ldots x_n)$$

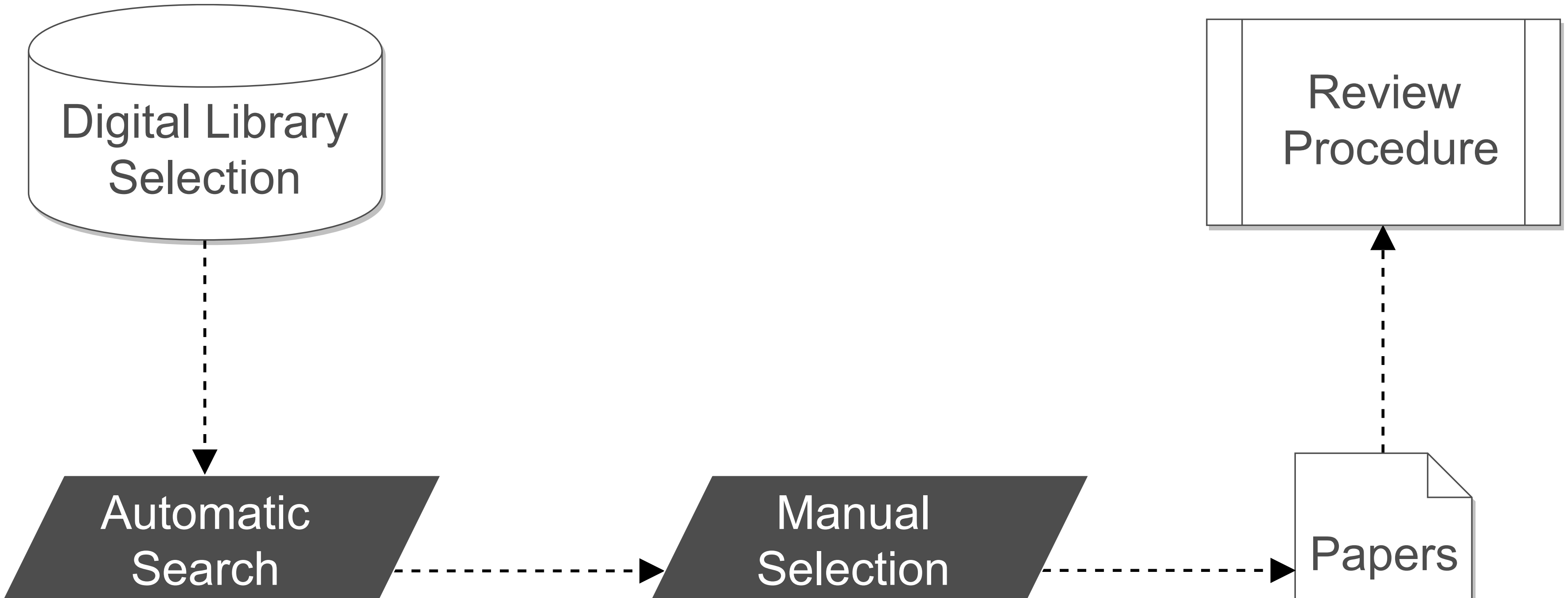
OBJECTIVES

For hyperparameter optimization:

1. `Summarize` recent methods
2. `Discuss` limitations
3. `Propose` improvements and *future* directions

METHODS

METHODS PROCESS



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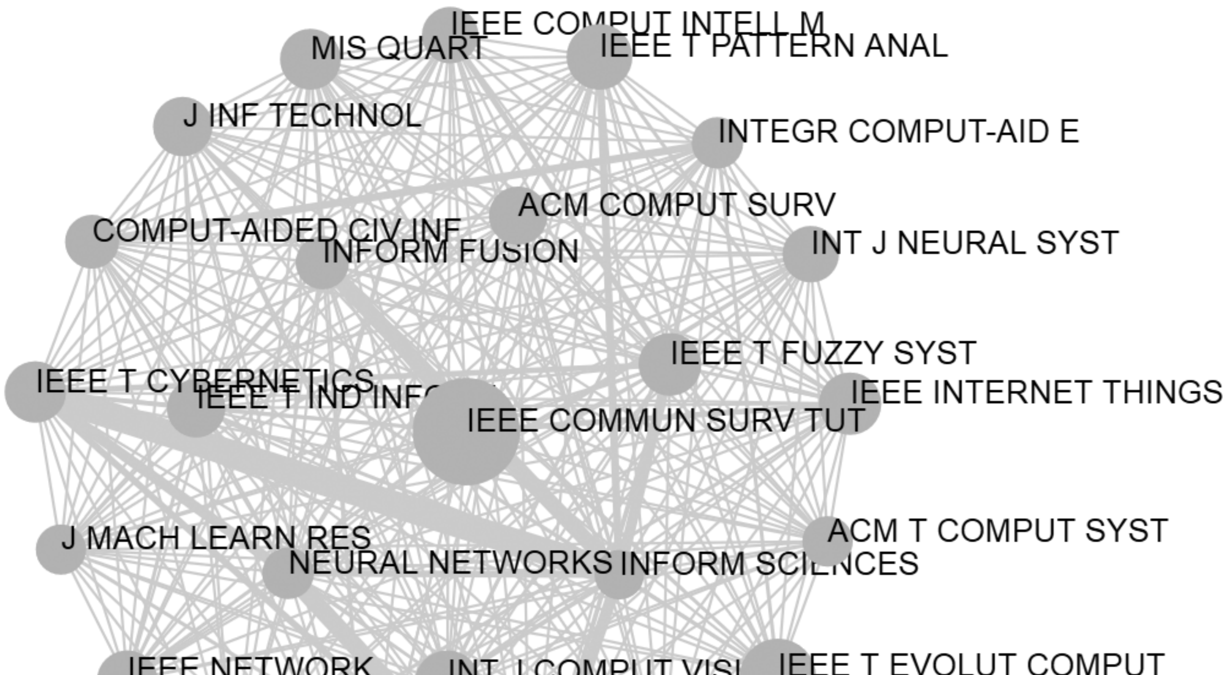
DIGITAL LIBRARY SELECTION



AUTOMATIC SEARCH QUERIES

Query	Value
`Publication`	**IEEE** or **ACM**
`Year`	2014 to October 5, 2017
`Title contains`	hyperparameter, optimization

MANUAL SELECTION CRITERIA

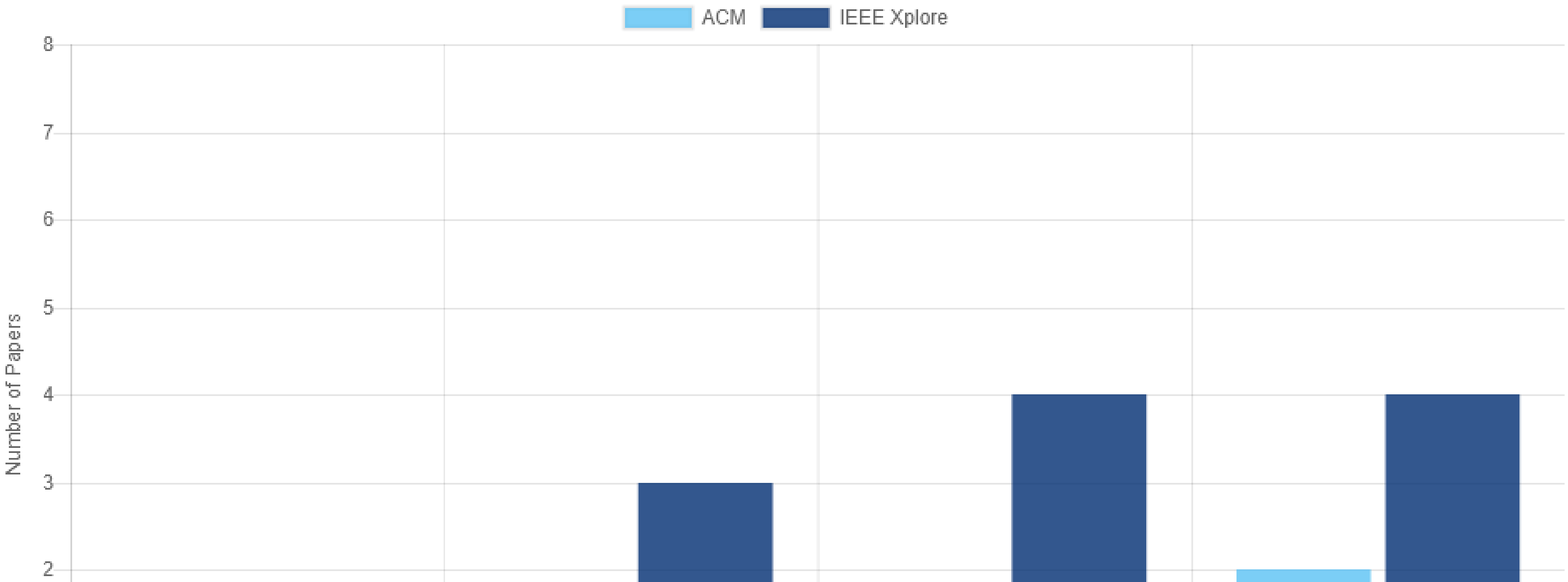
Criteria	Description
`Detailed`	specific methods and results, >= 8 pages
`Relevant`	mention hyperparameter optimization
`Practical`	experiments, benchmarks, applications

REVIEW PROCEDURE

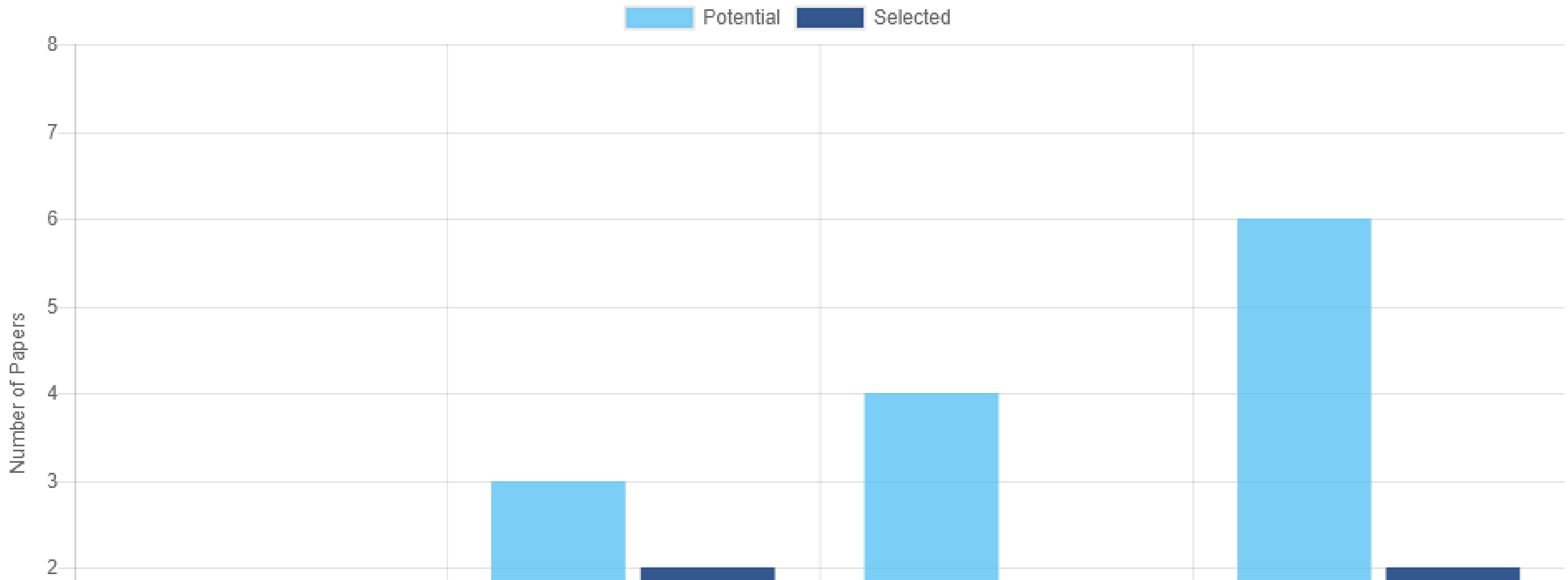
1. `Identify` methods
2. `Summarize` methods
3. `Summarize` experiments and results
4. `Discuss` limitations, improvements, directions

RESULTS

POTENTIAL PAPERS



SELECTED PAPERS



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HYPERPARAMETER OPTIMIZATION METHODS

1. `Simple`: **Exhaustive search**
2. `Advanced`: **Model or procedural based search**

SIMPLE METHODS

Method	Description
`Manual Search`	Trial and error
`Grid Search`	Predefined range of values
`Random Search`	Randomized range of values

Ref: [6]

MANUAL SEARCH

Hyperparameter	Values
x_1	5
x_2	10
x_3	15

GRID SEARCH

Hyperparameter	Values
x_1	5, 10, 15
x_2	3, 6, 9
x_3	2, 4, 6

RANDOM SEARCH

Hyperparameter	Values
x_1	6, 10, 8, 12
x_2	9, 17, 1
x_3	21, 5

ADVANCED METHODS

Method	Description
`Assumption`	Expert assumptions for particular cases
`Evolutionary`	Procedurally generated hyperparameters
`Sequential Model`	Sequentially guided hyperparameters

ASSUMPTION BASED OPTIMIZATION

- Specific algorithms, data, and cases
- Select $x \ldots x_n$ based on assumptions
- e.g. Distribution assumptions

Ref: [1]

EVOLUTIONARY BASED OPTIMIZATION

- **M**imic biological evol*u*tion
- **E**volve and nat*u*rally select $x \ldots x_n$
- e.g. **G**enetic algorithms, particle swarm

Ref: [7]

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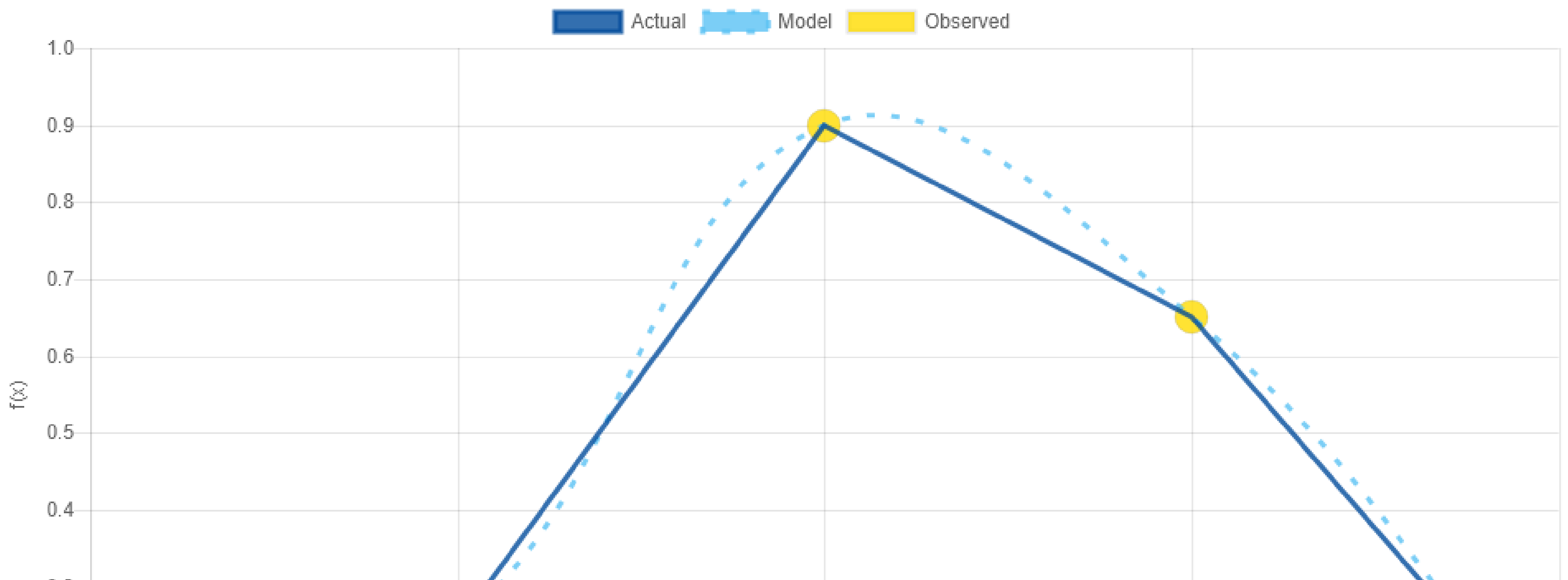
SEQUENTIAL MODEL BASED OPTIMIZATION (SMBO)

- Model performance function f using $x \ldots x_n$
- **P**redict next best set of hyperparameters
- e.g. **B**ayesian optimization

Ref: [8-10]

SMBO EXAMPLE



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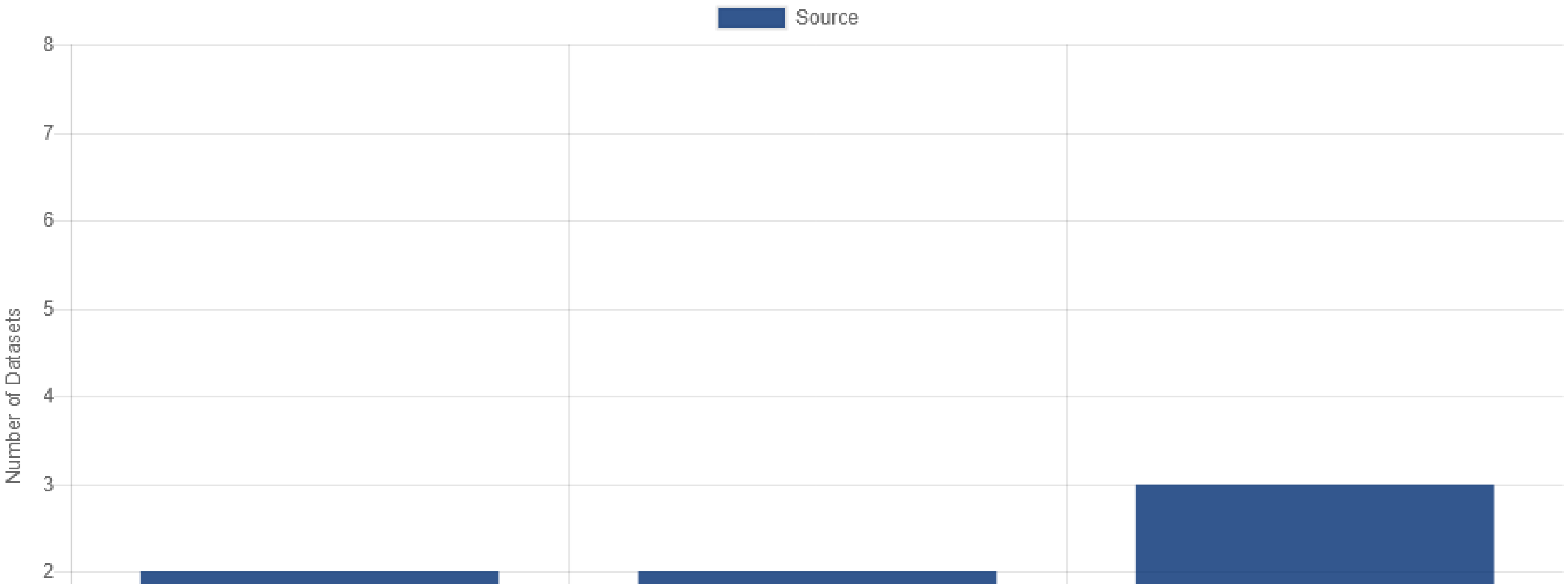
SMBO IMPROVEMENTS

- Transfer learned hyperparameters [1]
- Discover better starting hyperparameters [2]
- Measure transfer hyperparameters influence [3]
- Consider hyperparameter inter-dependency [4]

SMBO EXPERIMENTS

- Improved performance (e.g. ~10-20%)
- Better hyperparameters than simple methods
- Same time and iteration constraints

SMBO DATA



DISCUSSION

LIMITATIONS

- Man*u*al constraints selection
- Scalability
- Dataset variability

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MANUAL CONSTRAINTS

- Hyperparameters $x \dots x_n$
- Performance measure f
- Set of constraints C
- Iteration or steps t

$$\underset{x \dots x_n \in C}{\operatorname{argmax}} f(x \dots x_n) \text{ given } t$$

IMPROVEMENTS AND FUTURE DIRECTIONS

- Automated Machine Learning
- Combining methods
- Sampling

CONCLUSION

- Reviewed 5 papers
- **SMBO** as an effective framework
- Constraints and scalability
- Automated Machine Learning

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THANK YOU

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github.com/rrwen/slides-rmcs-litreview

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