Course wrap-up

STAT 4710

December 5, 2023

Where we are

- ✓ **Unit 1:** Intro to modern data mining
- ✓ **Unit 2:** Tuning predictive models
- ✓ **Unit 3:** Regression-based methods
- ✓ **Unit 4:** Tree-based methods
- ✓ **Unit 5:** Deep learning

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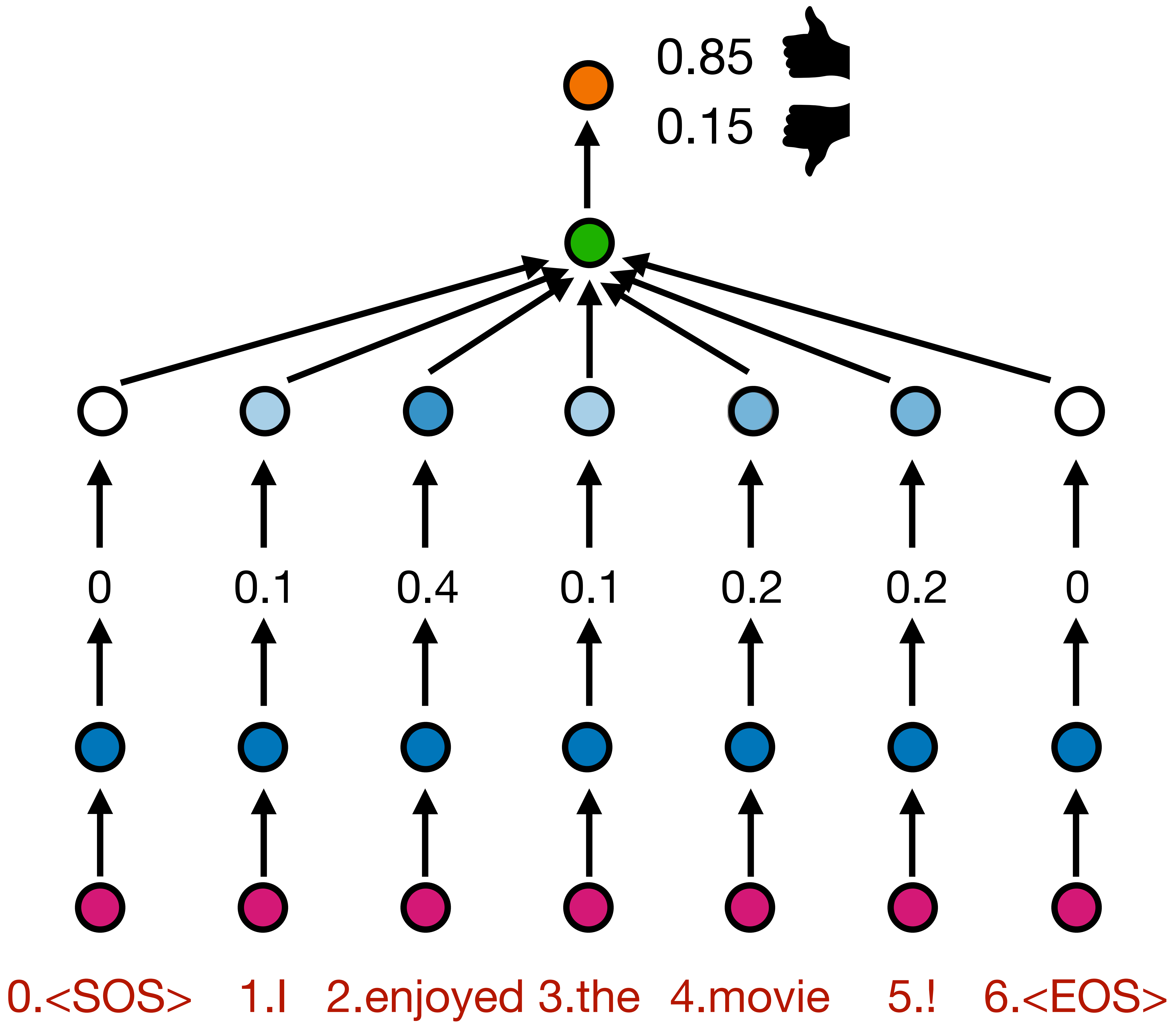
Today's lecture:

- Deep learning bonus material: Transformers beyond NLP.
- Looking back at STAT 4710
- Looking beyond STAT 4710

Transformers beyond NLP



Transformers beyond NLP

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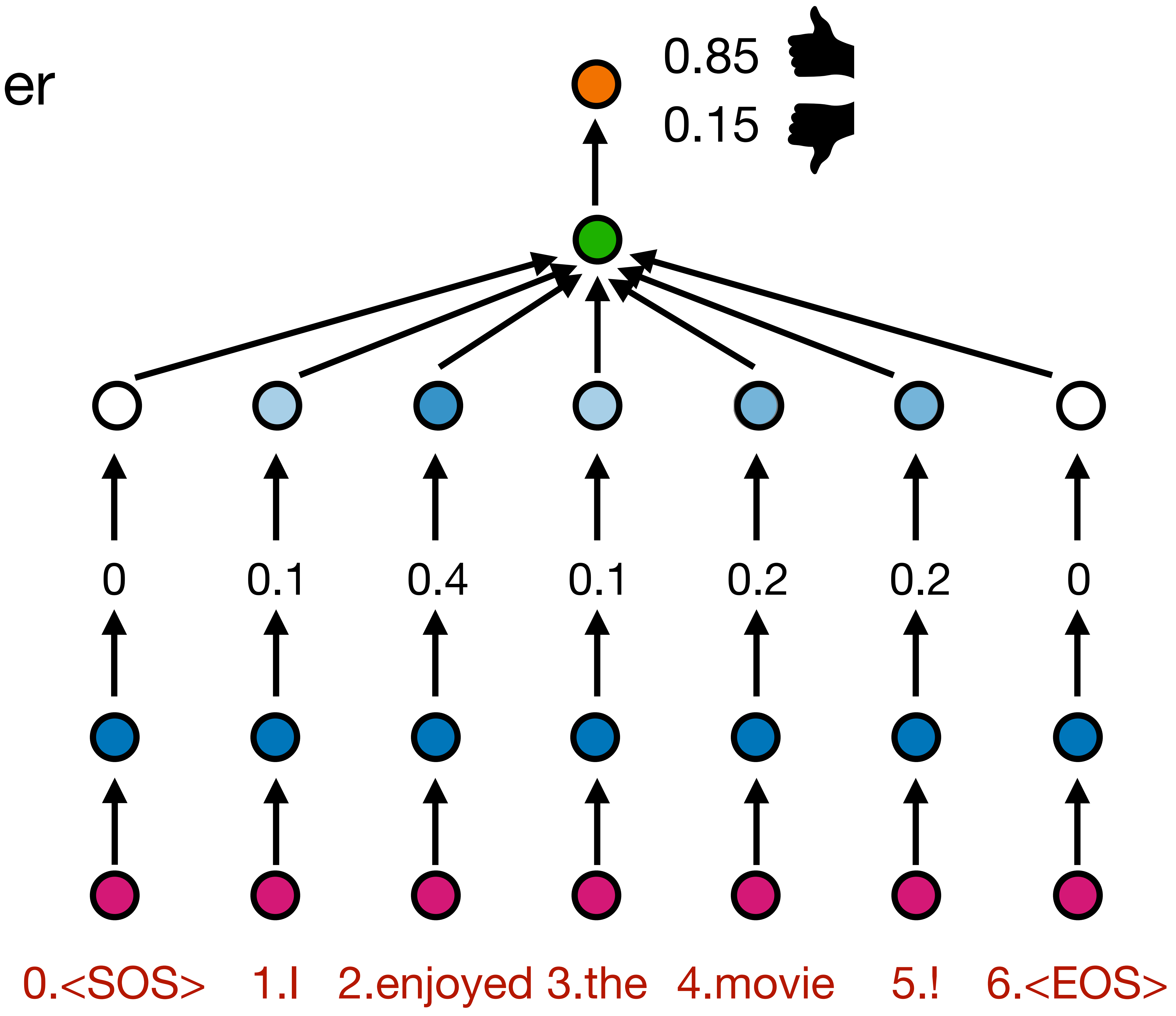

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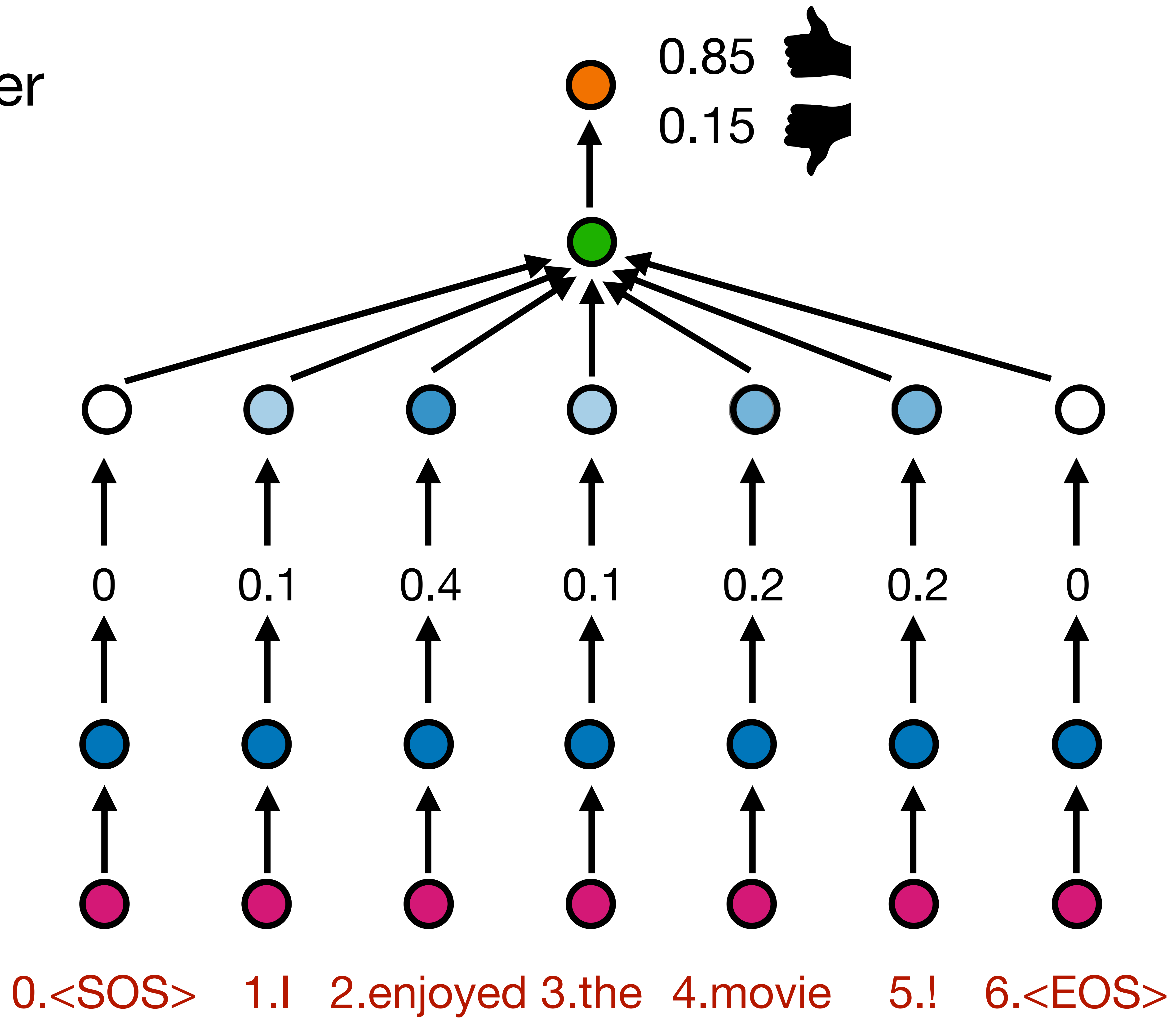

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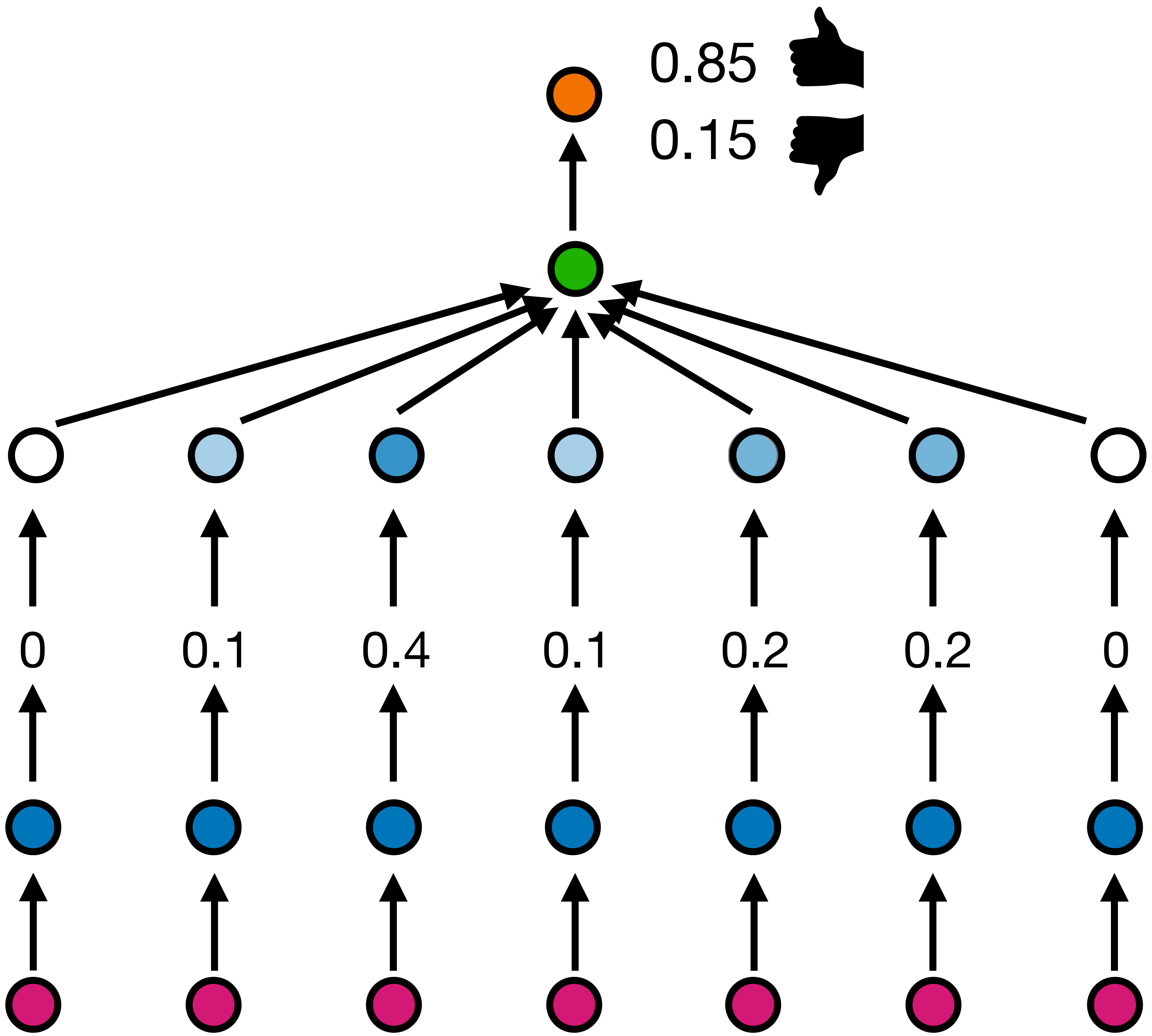

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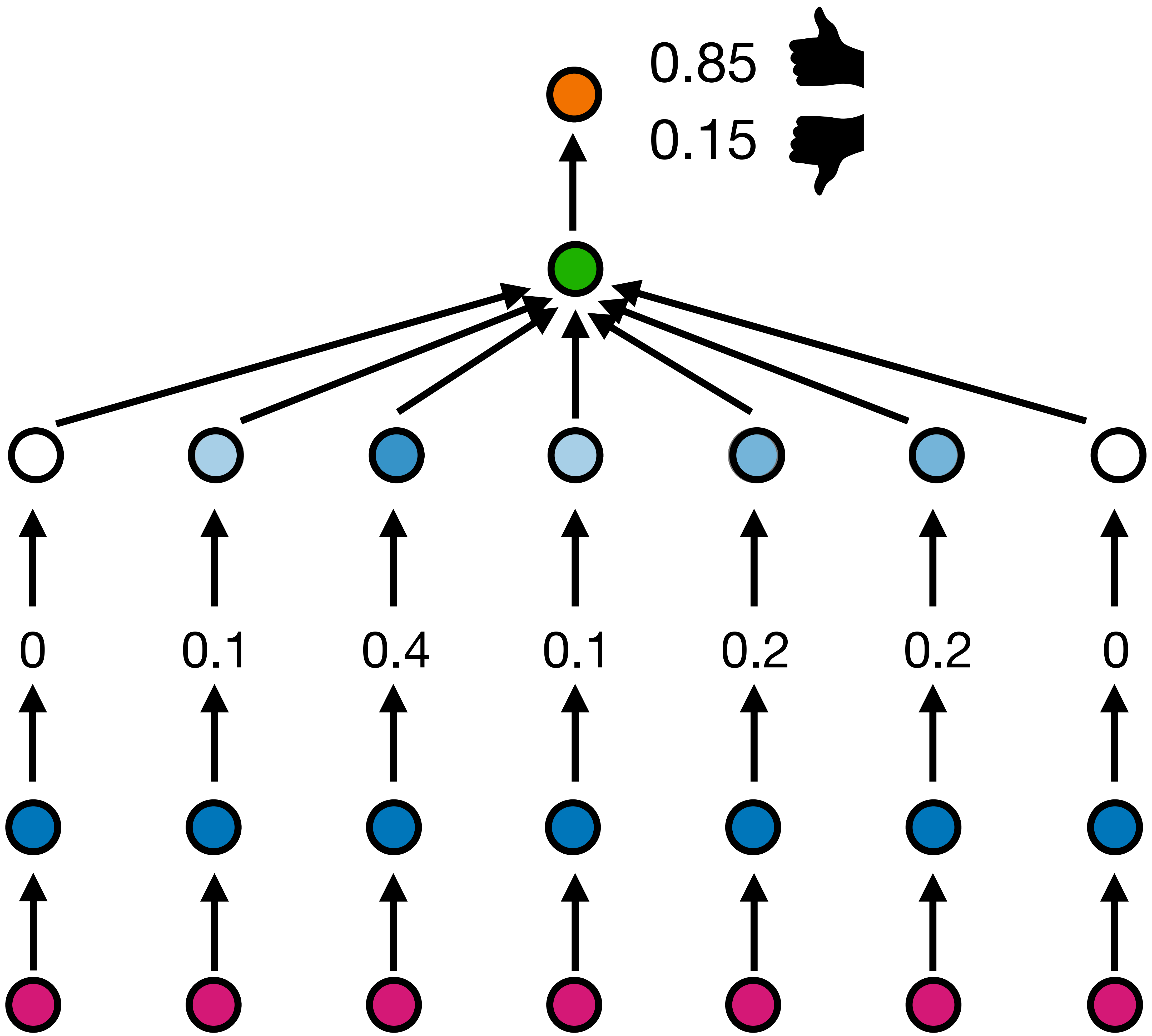

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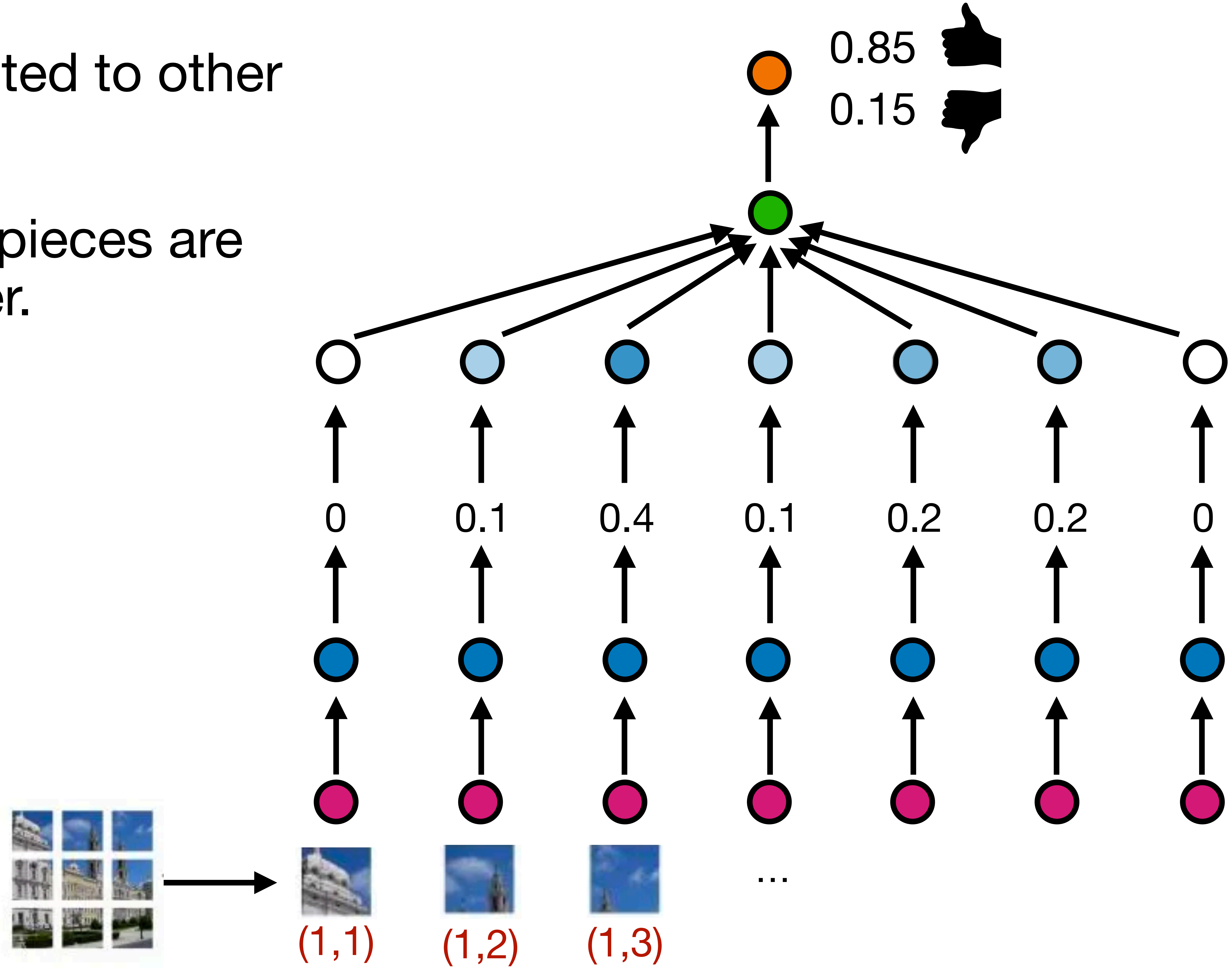

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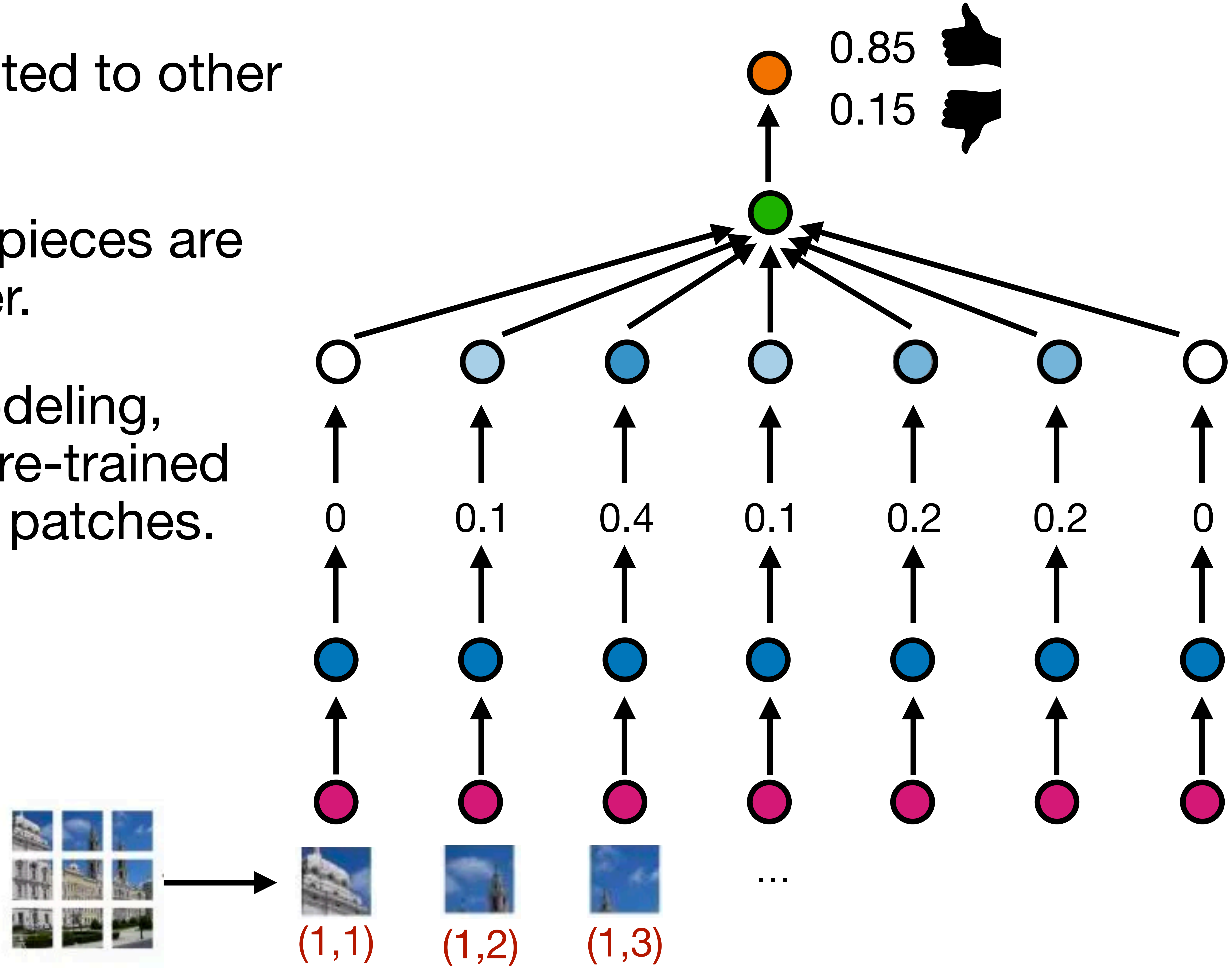

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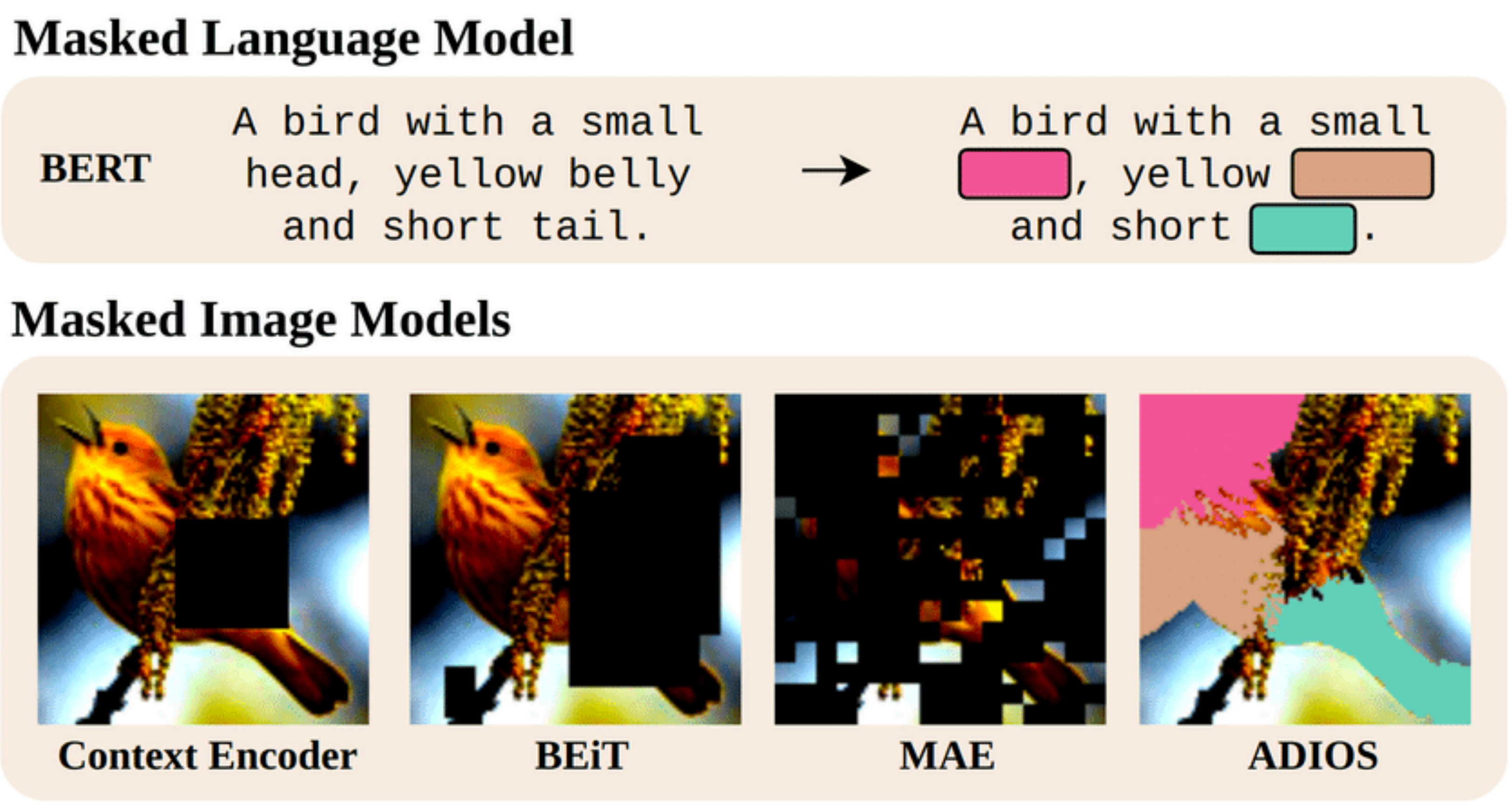

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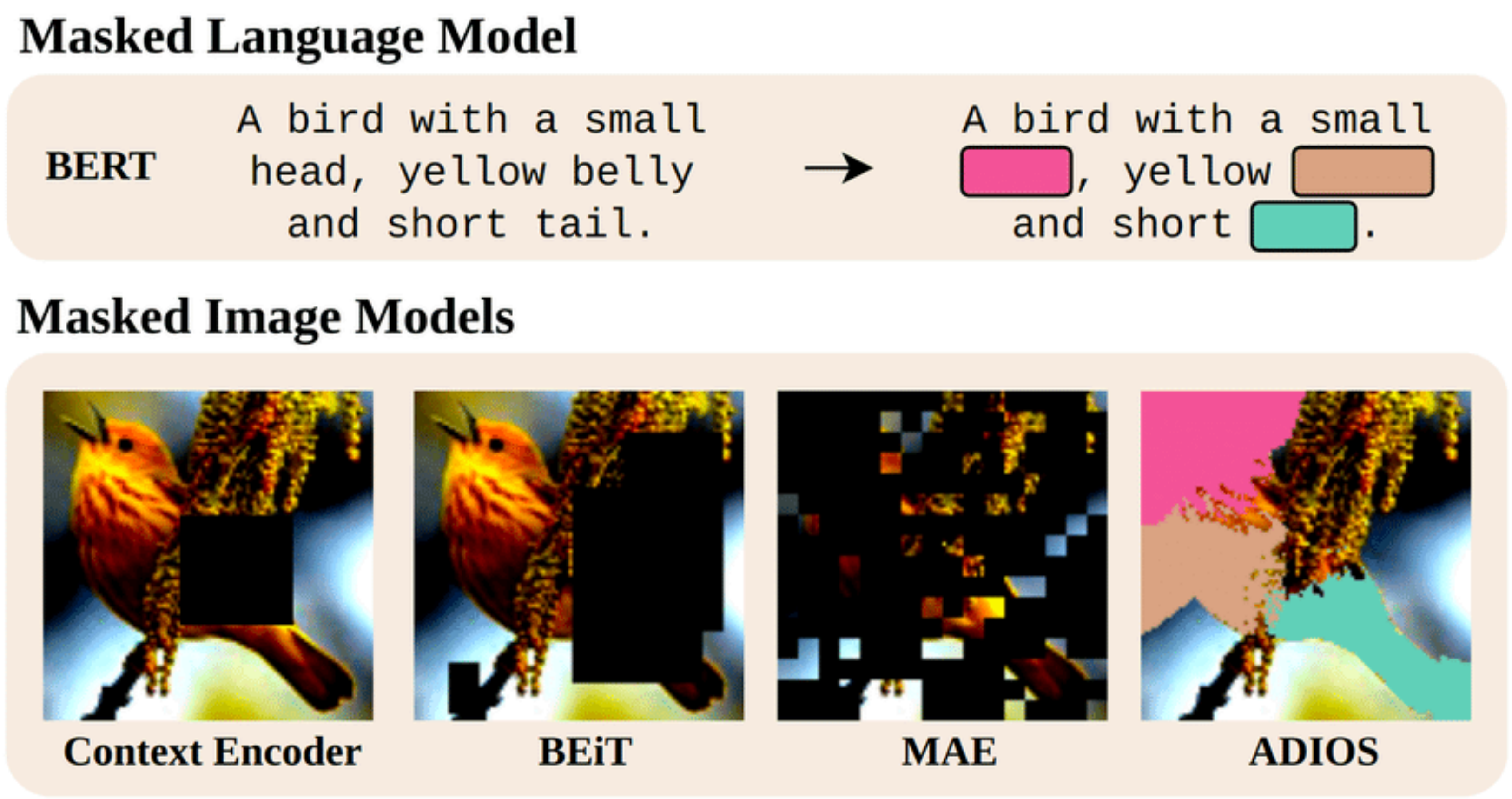

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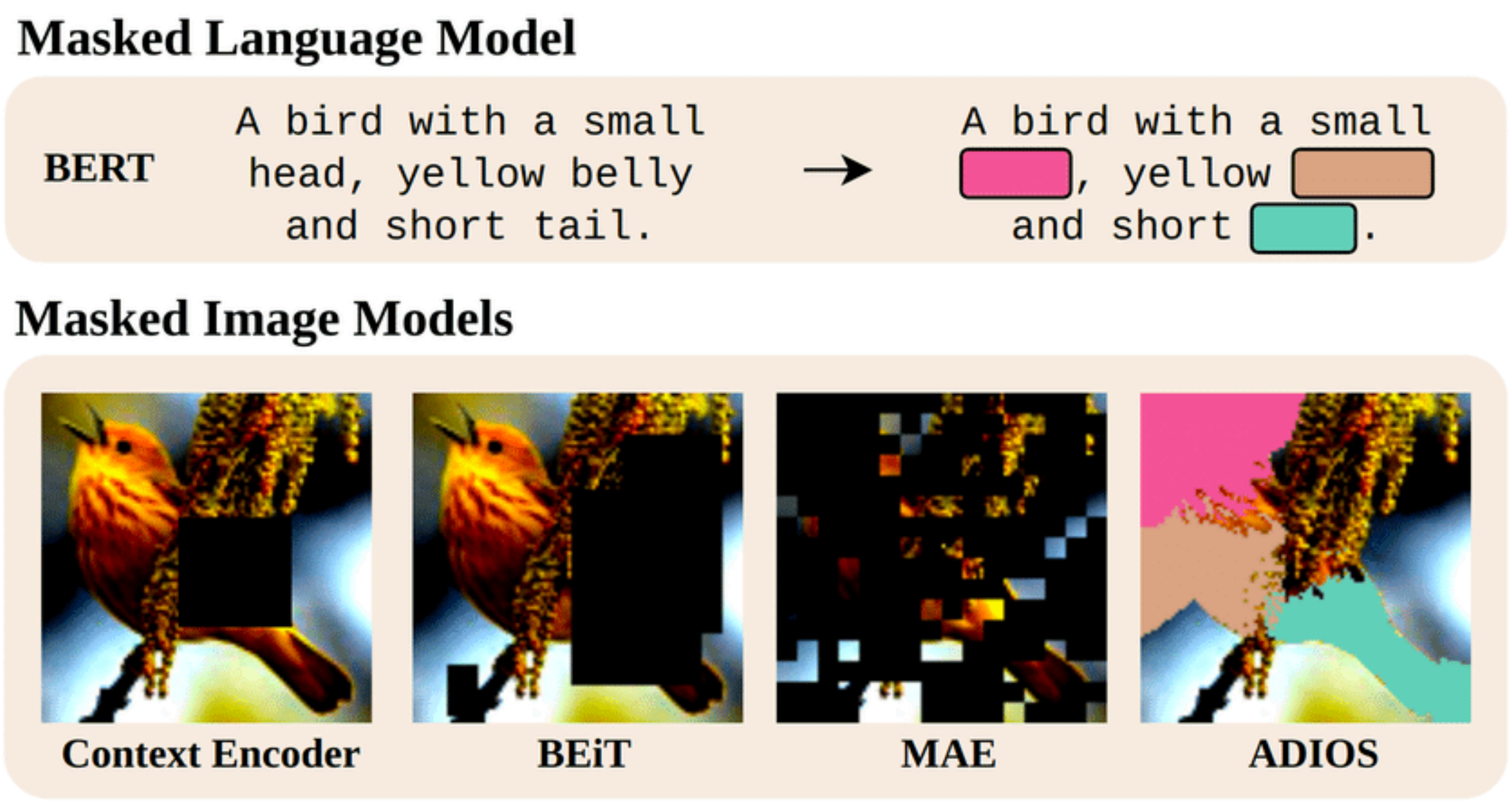

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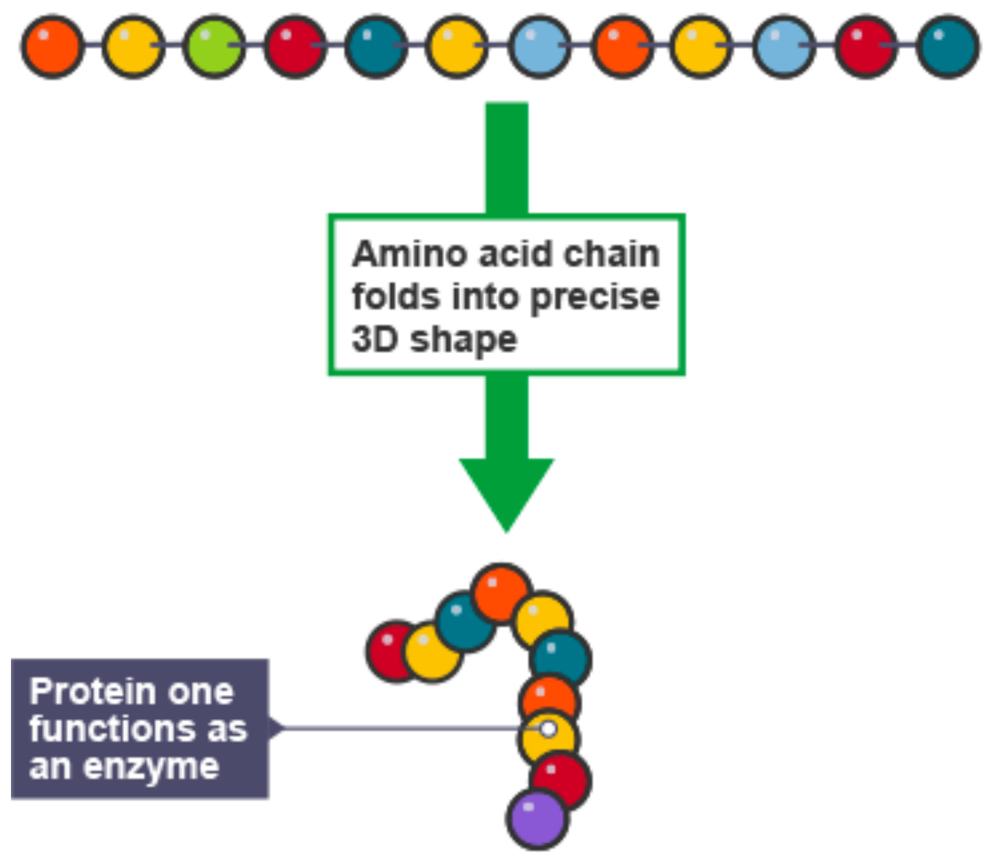

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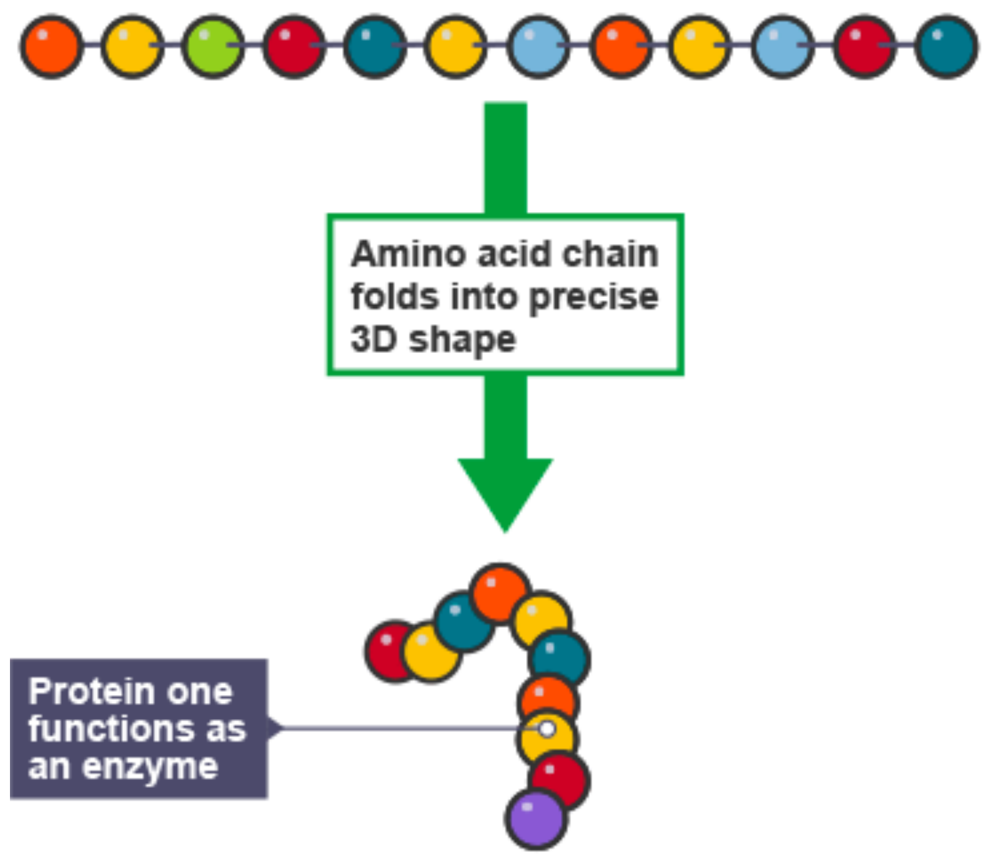


COVID-19

Science

NEWS | BIOLOGY

'The game has changed.' AI triumphs at solving protein structures

In milestone, software predictions finally match structures calculated from experimental data

30 NOV 2020 · BY ROBERT F. SERVICE

Looking back at STAT 4710

Themes of the class, and a lingering question

1. Regression and classification
2. Training predictive models
3. Model complexity
4. Bias-variance trade-off
5. Model selection and model assessment
6. Interpretability of predictive models
7. R programming tools
8. Working with data

Conceptual

Practical

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Lingering question: What is the best prediction method?

Theme: Regression and classification

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Many of the same intuitions apply for regression and classification.

Theme: Training predictive models

Define class of predictive models $f_\beta(X)$ indexed by some parameter vector β.

Find member of this class that best fits the training data, as measured by the loss function L of predictions given true responses, possibly regularized:

$$\widehat{\beta} = \arg\min_{\beta} \frac{1}{n} \sum_{i=1}^{n} L(Y_i, f_\beta(X_i)) + \lambda \cdot \text{penalty}(\beta).$$

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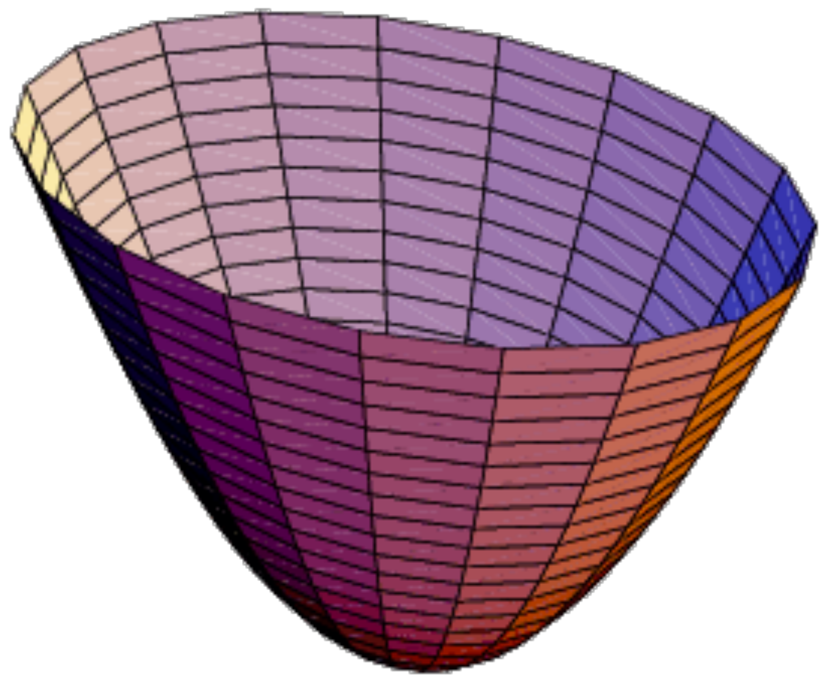
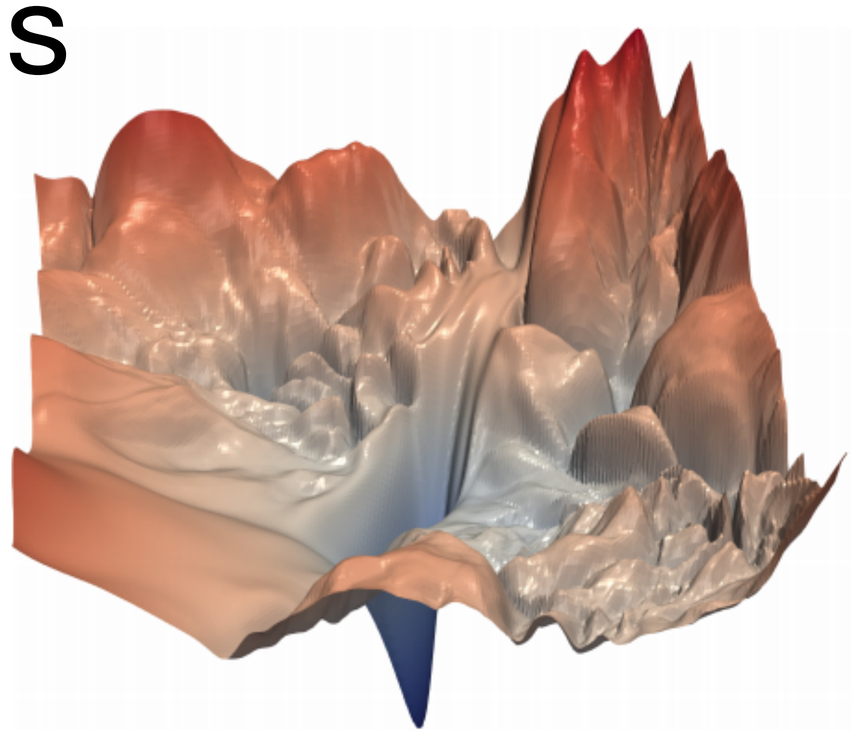
Convex (optimization is easy)

- Linear and logistic regression
- Linear and logistic regression with ridge or lasso penalties



Not convex (optimization is hard)

- Tree-based methods
- Neural networks



https://arxiv.org/abs/1712.09913

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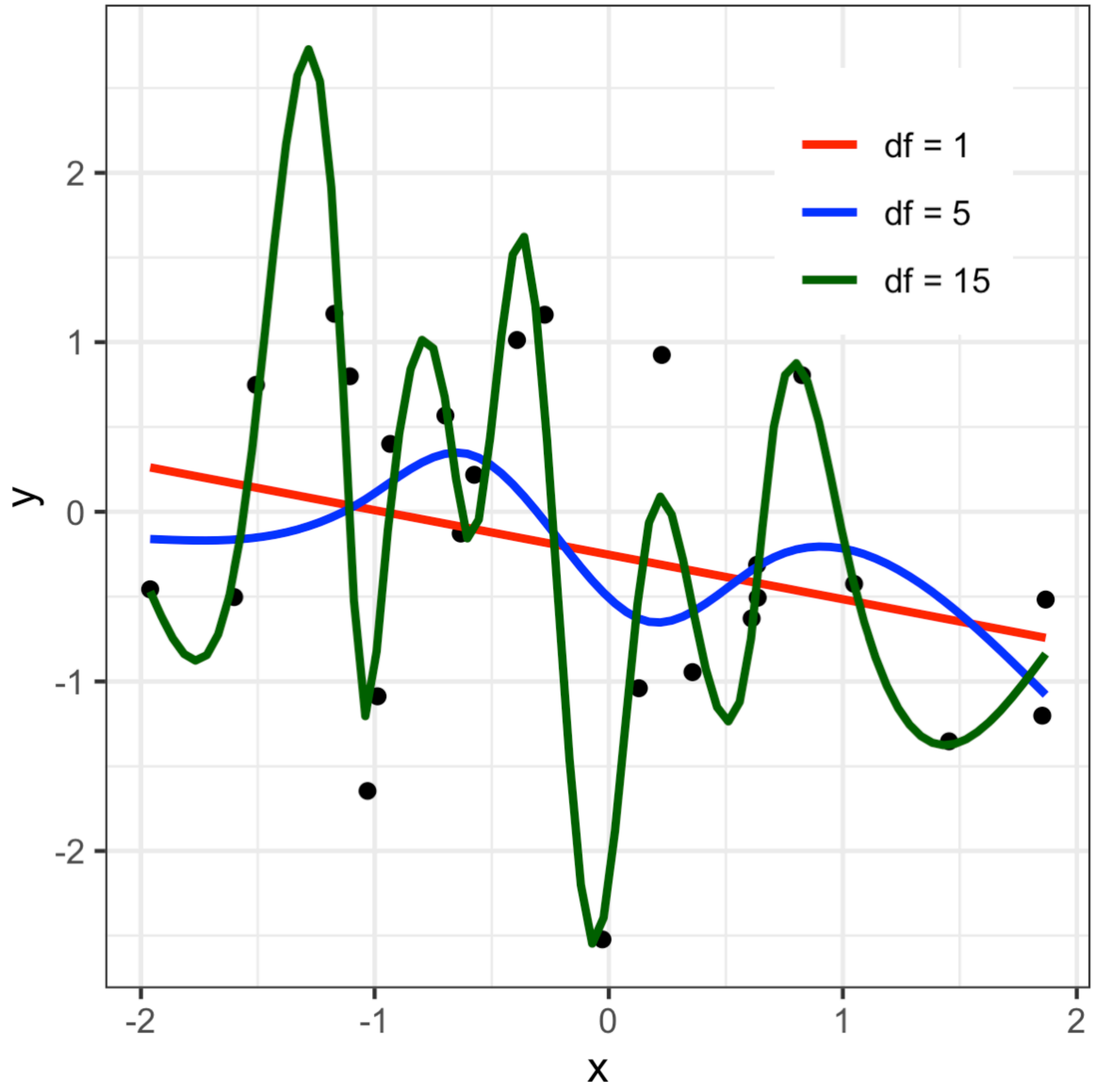

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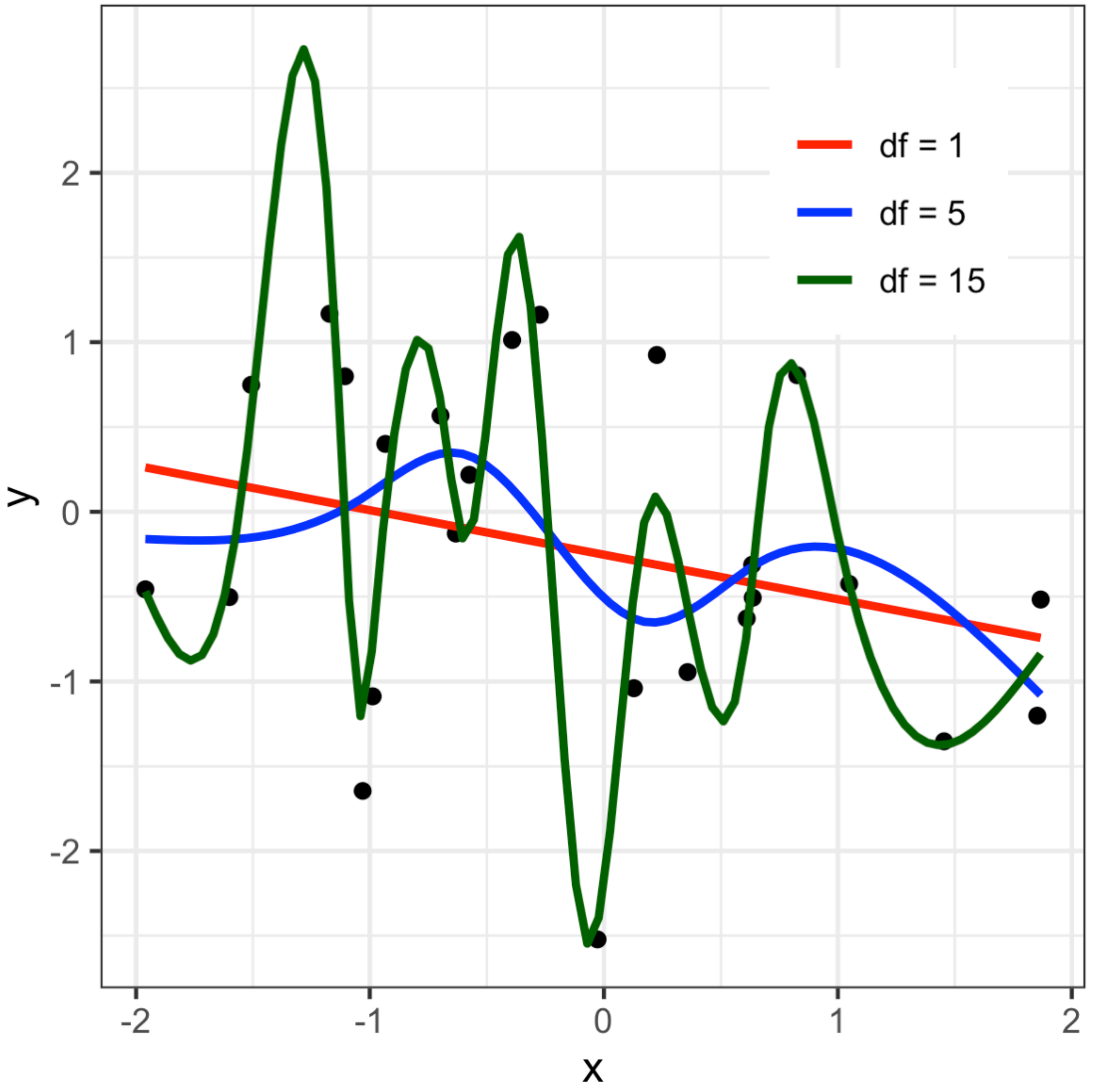

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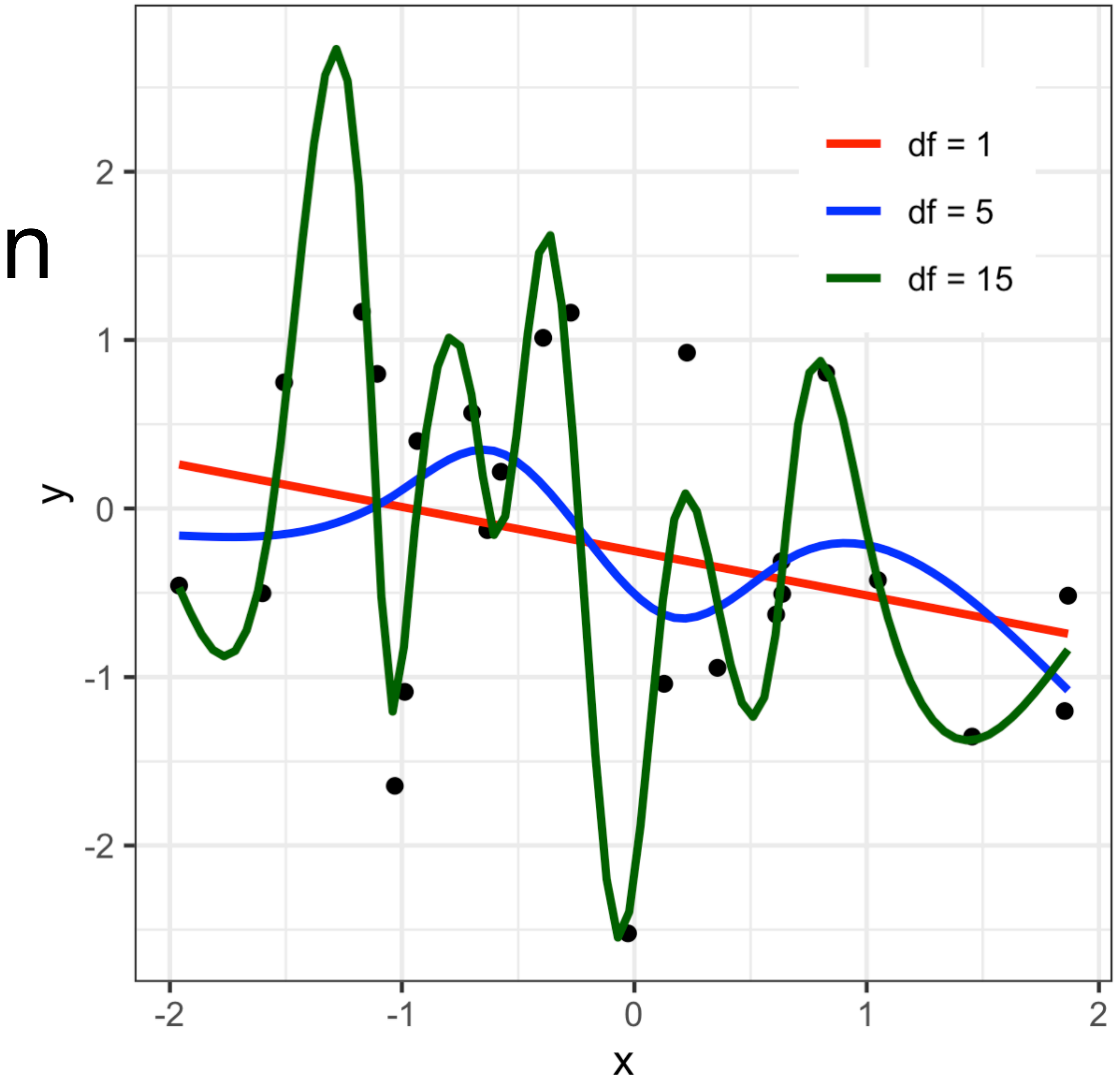

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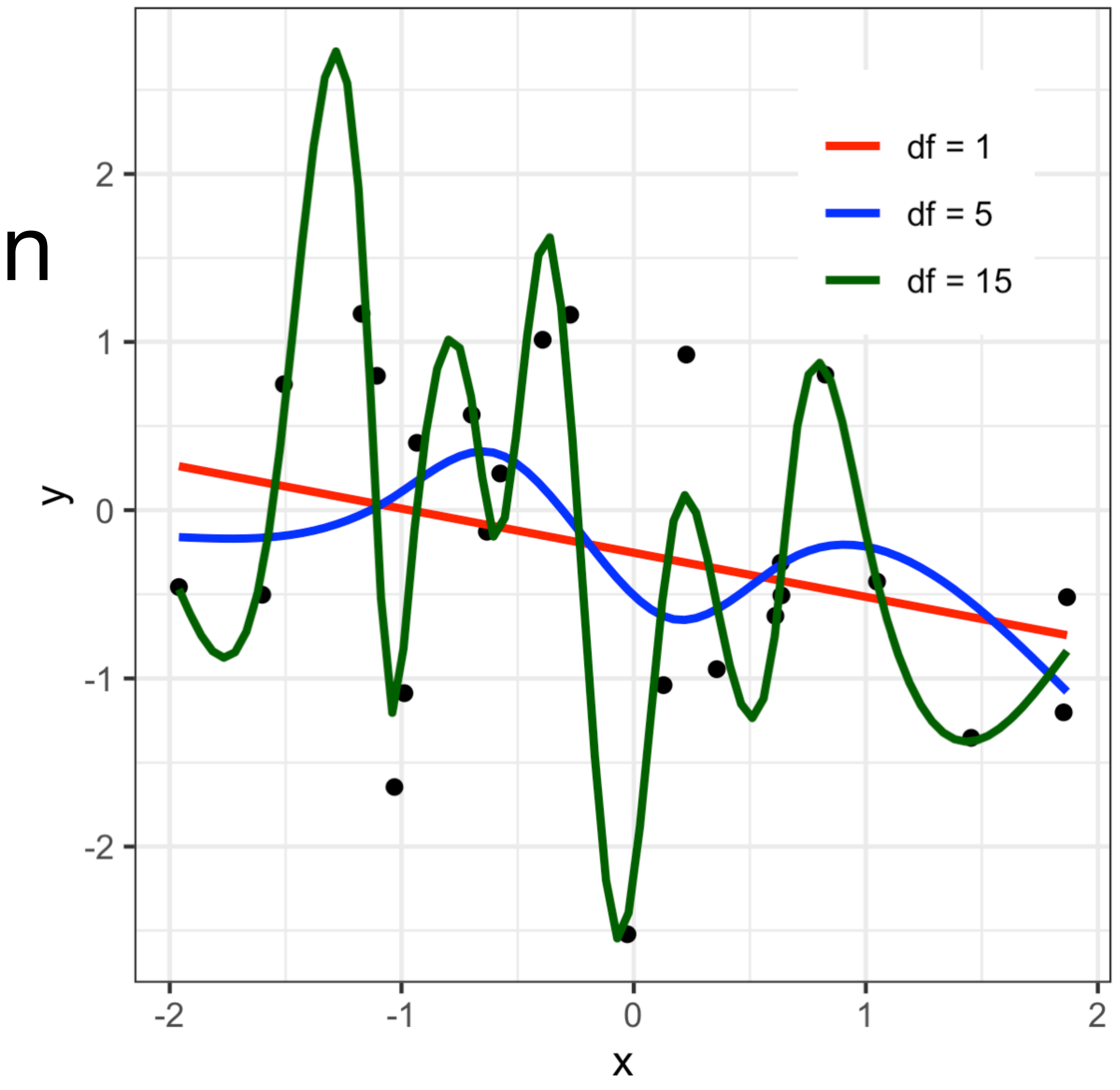

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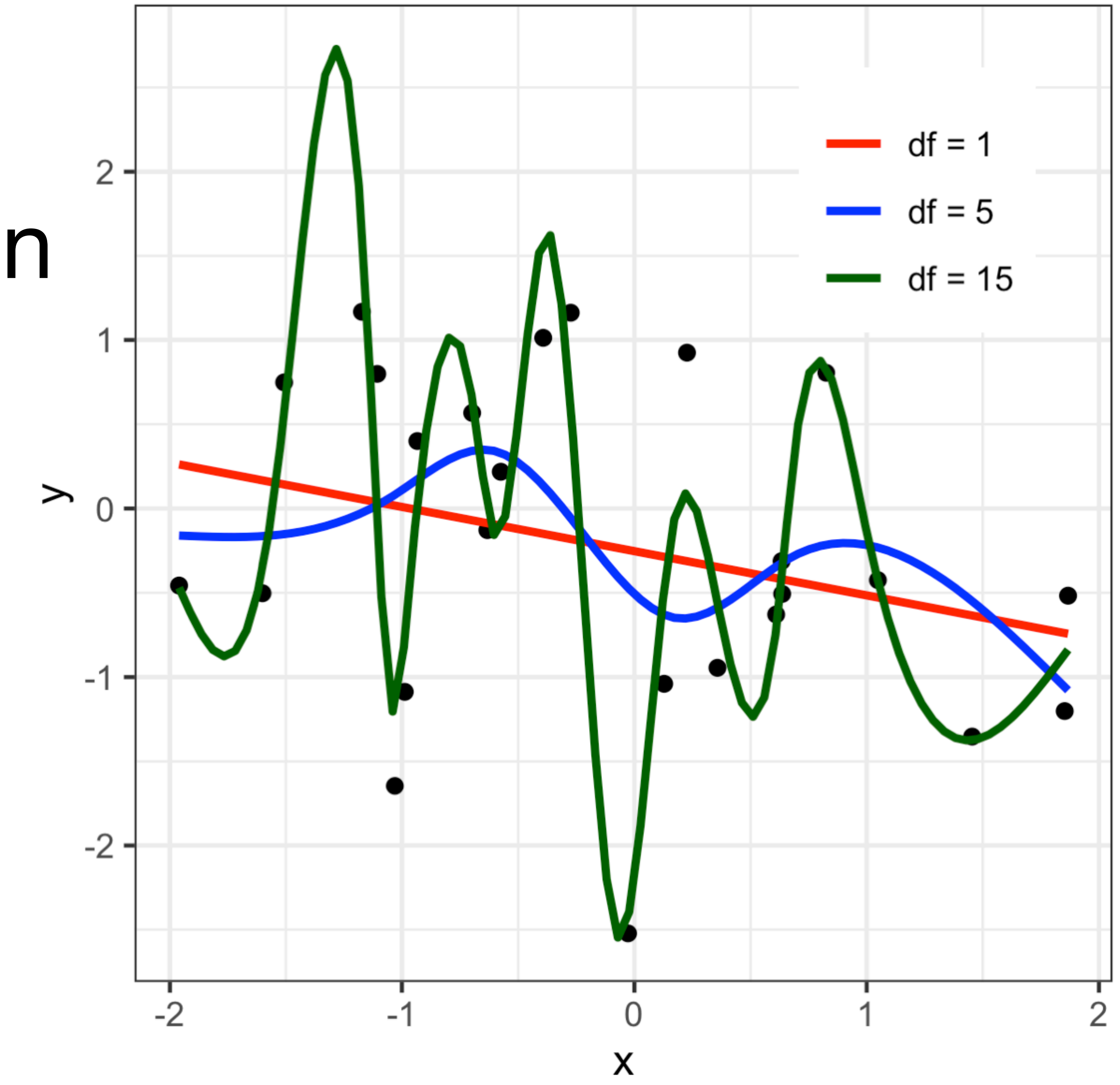

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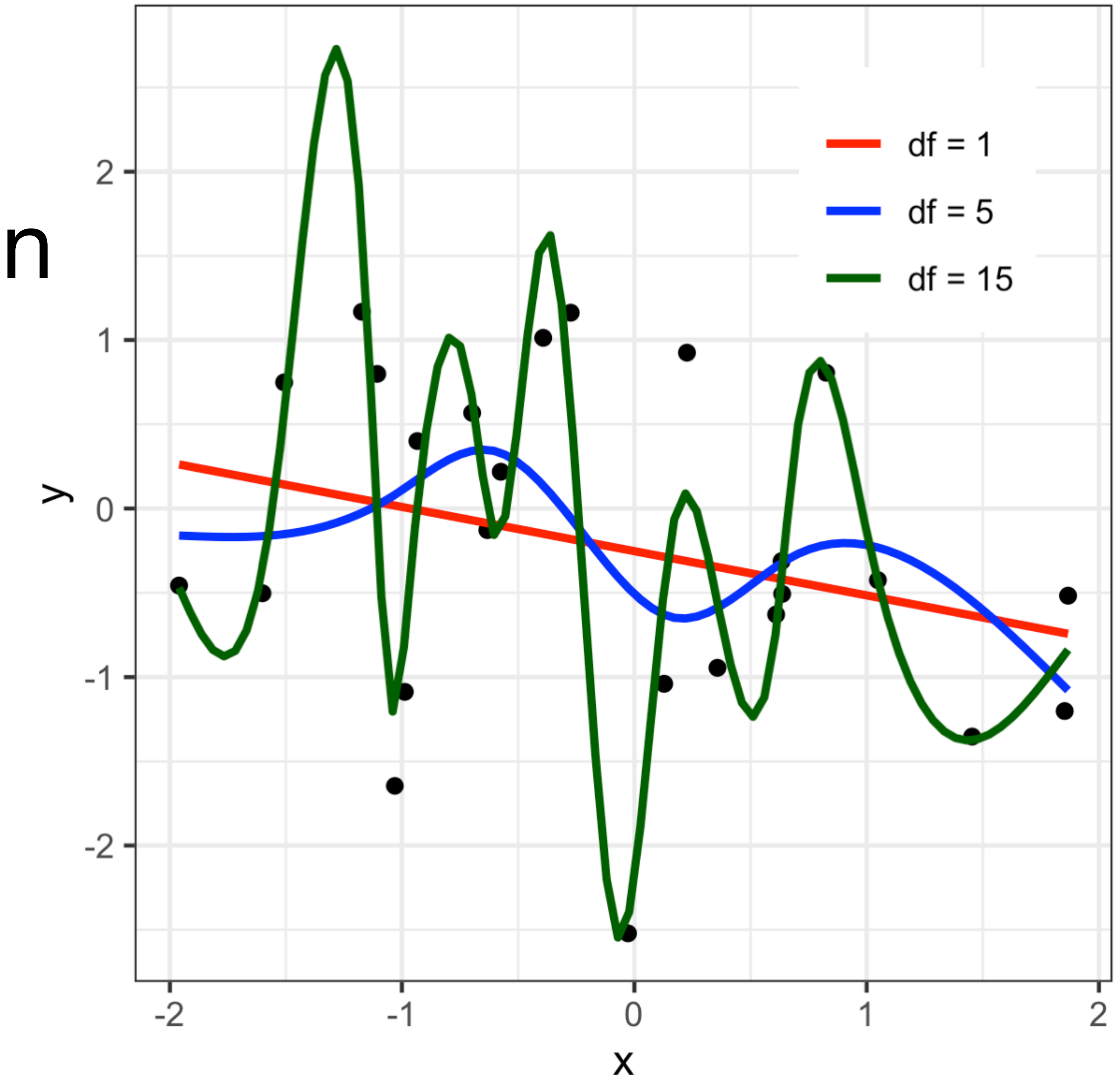

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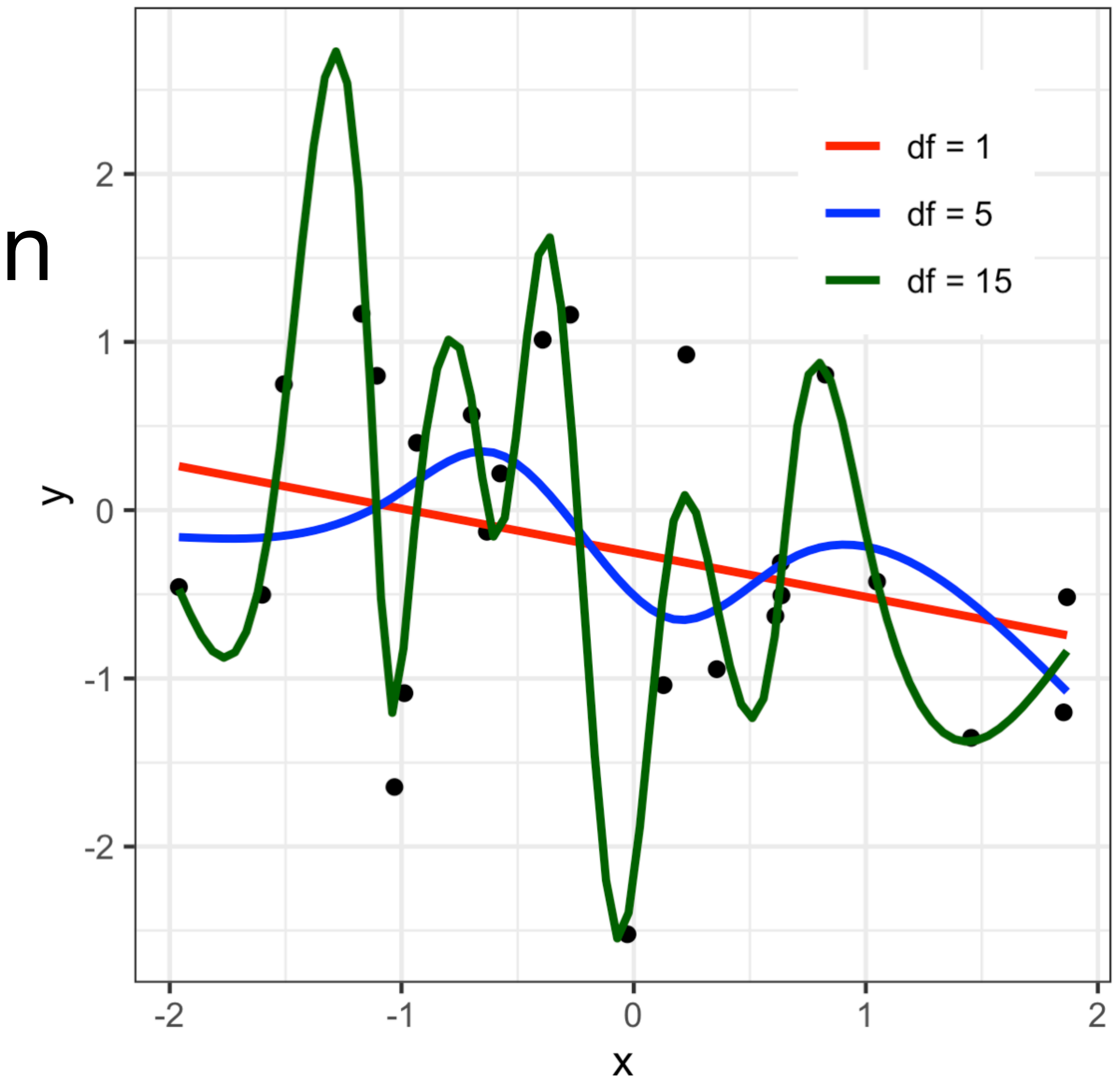

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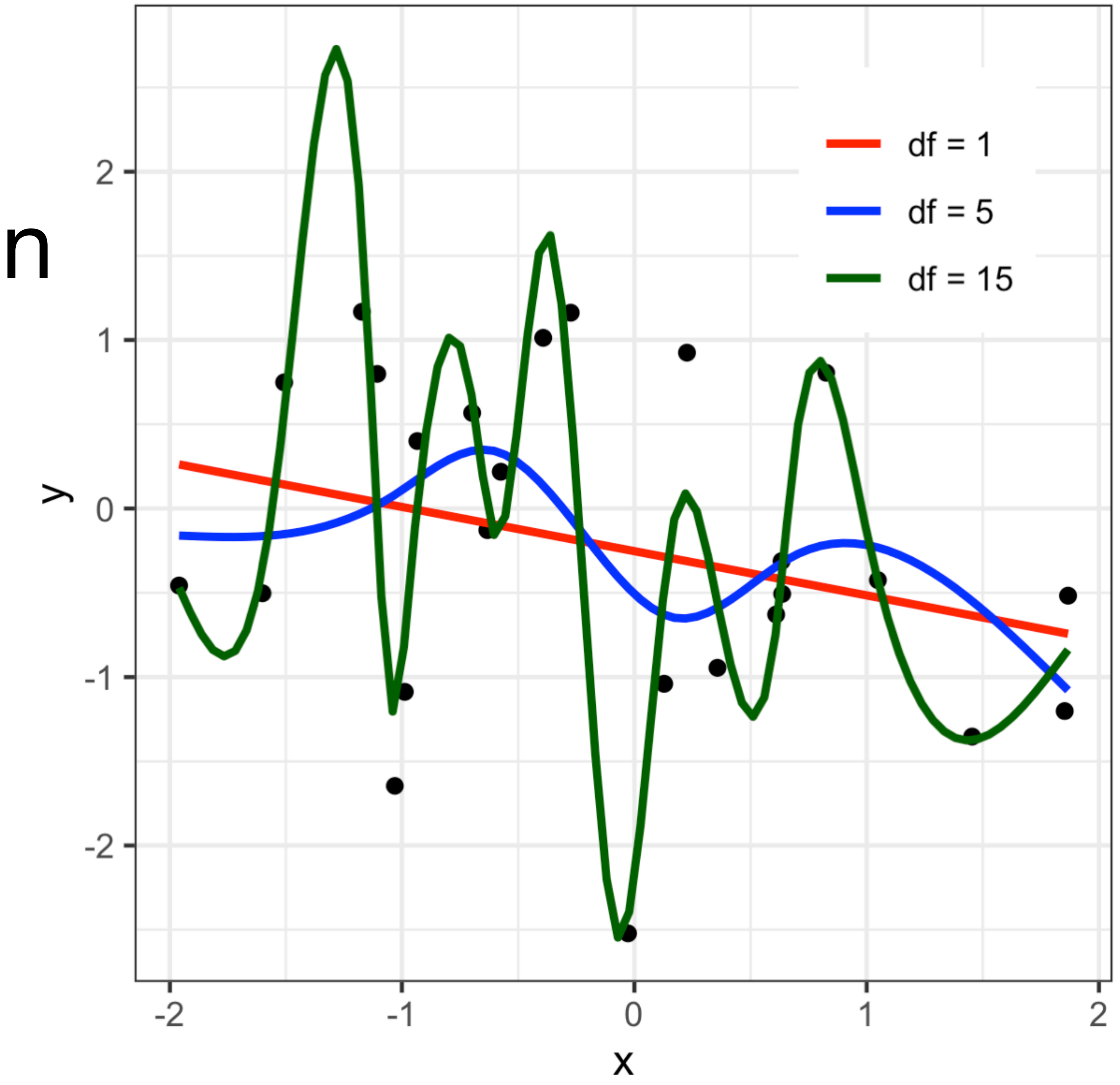
- Implicit regularization, e.g. sub-sampling features during random forest model training



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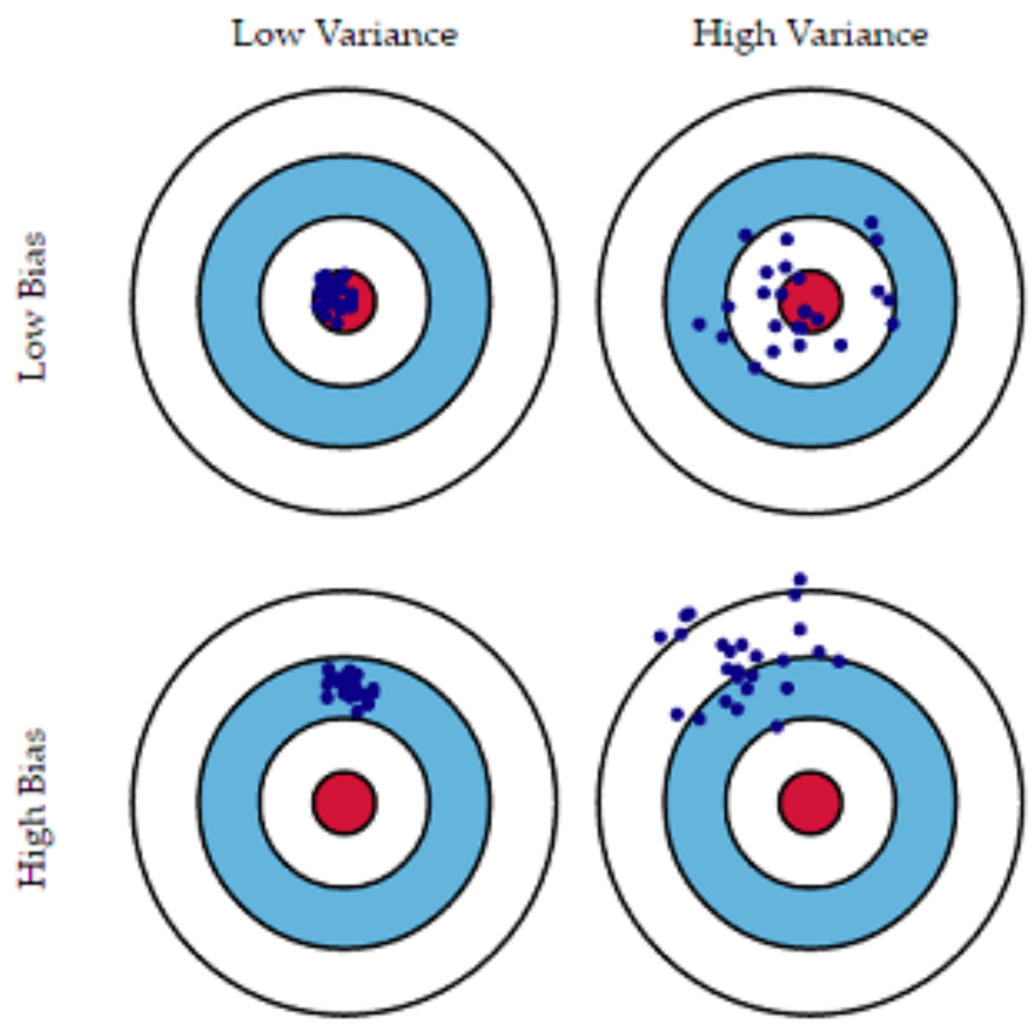

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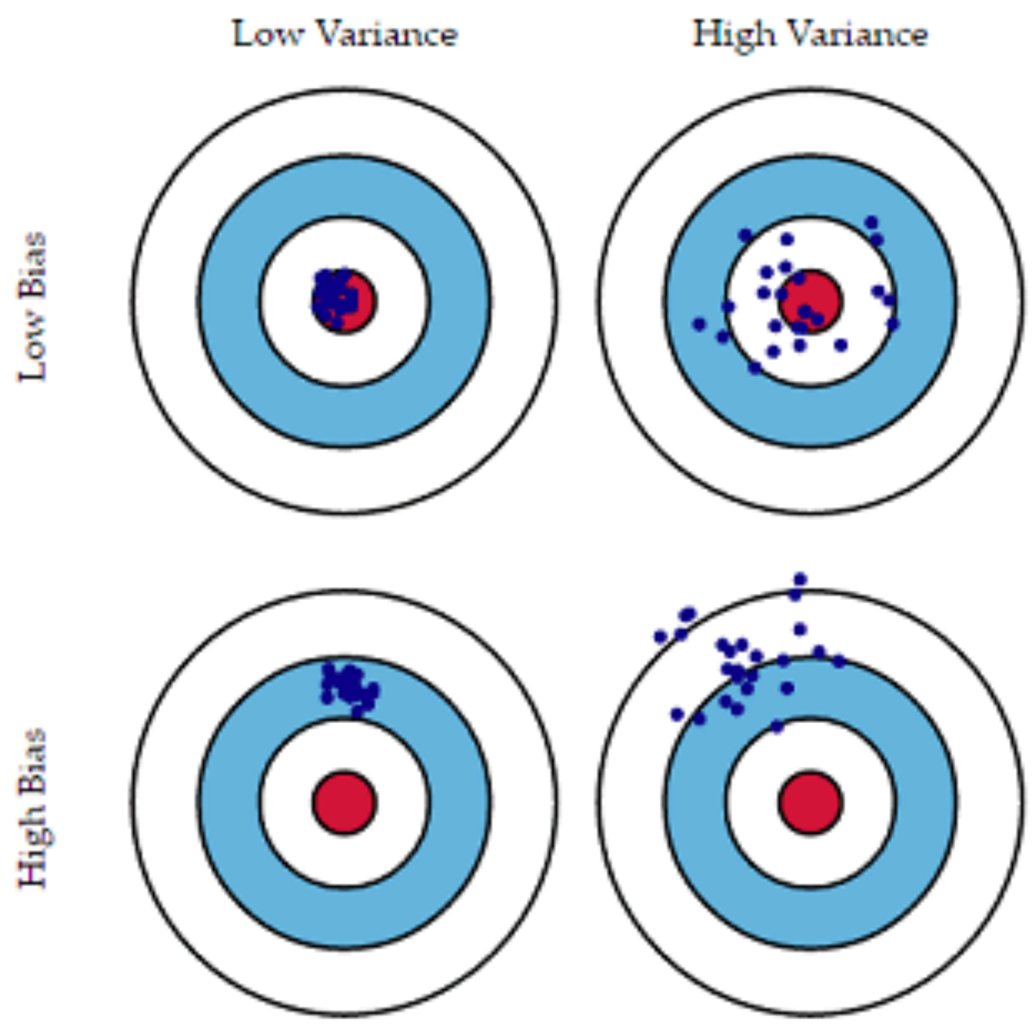

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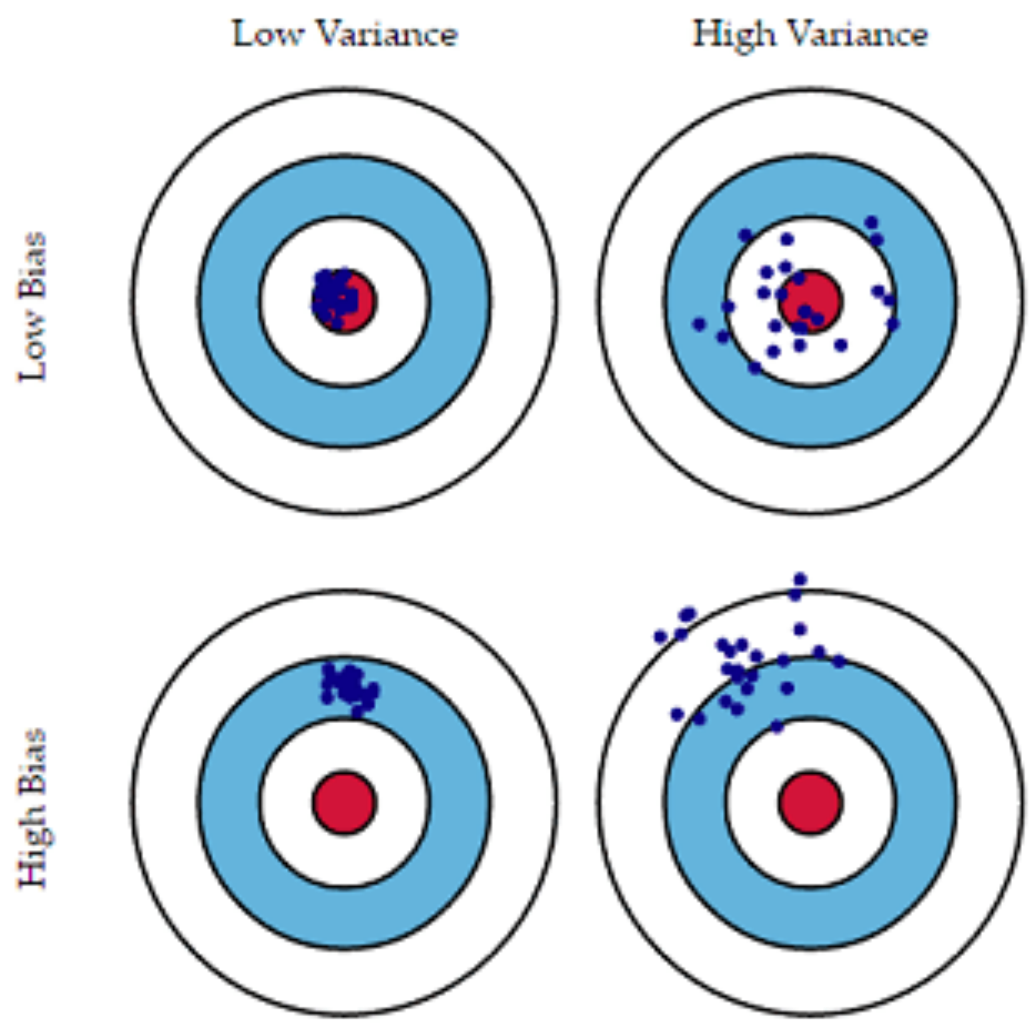

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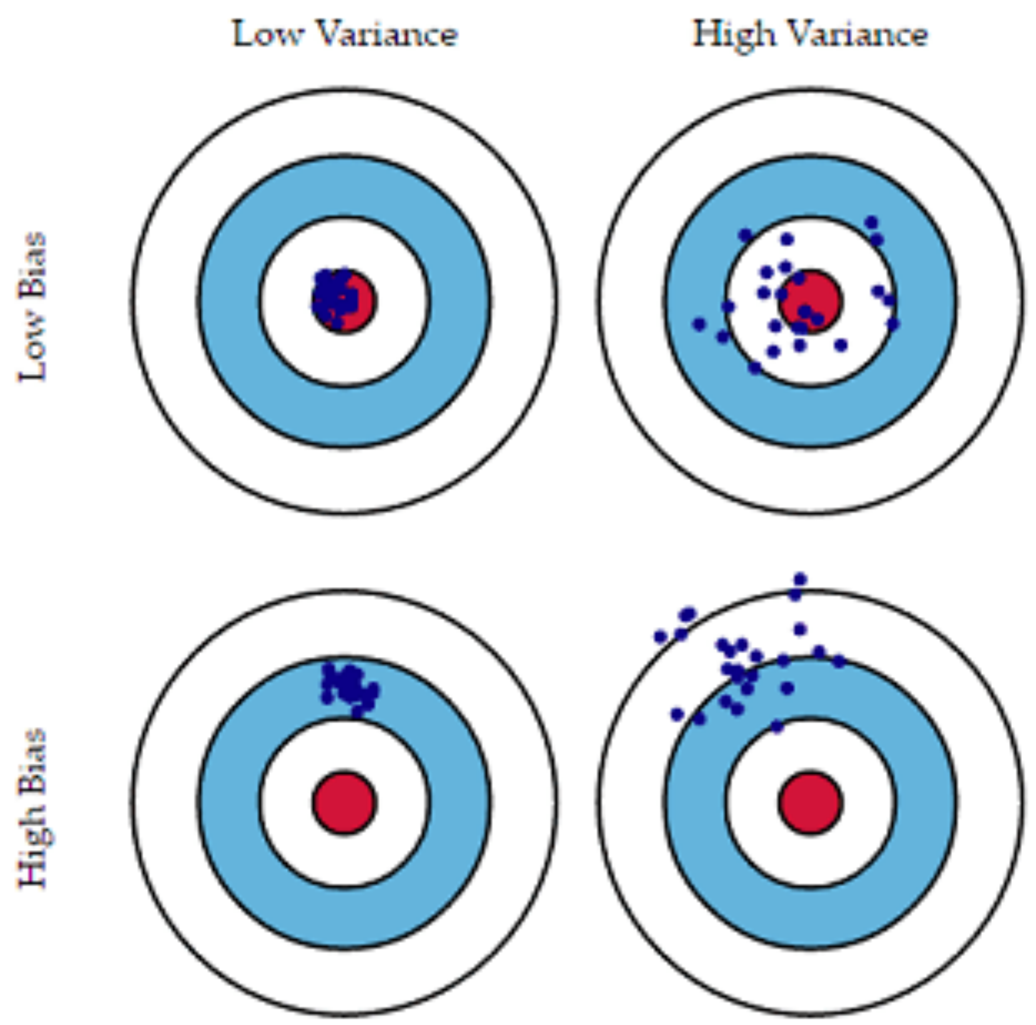

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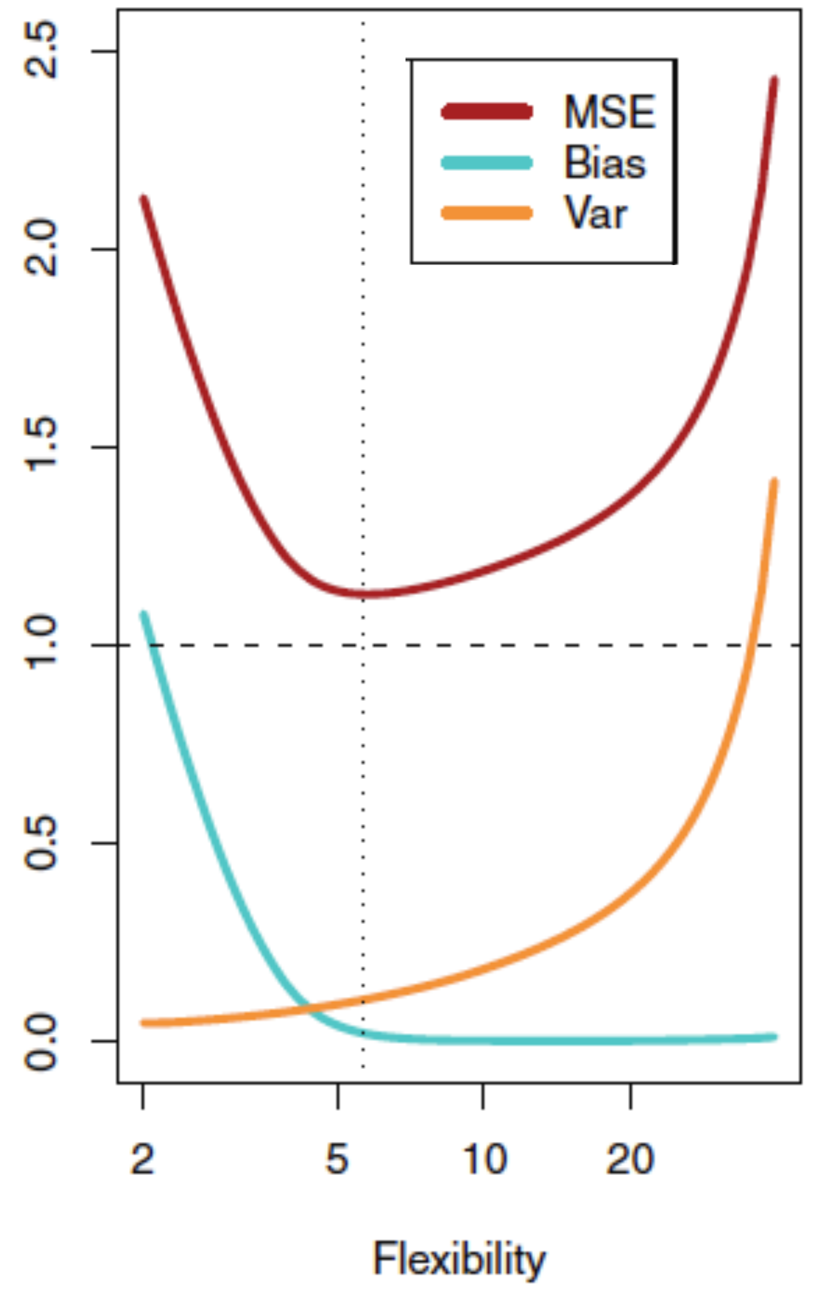

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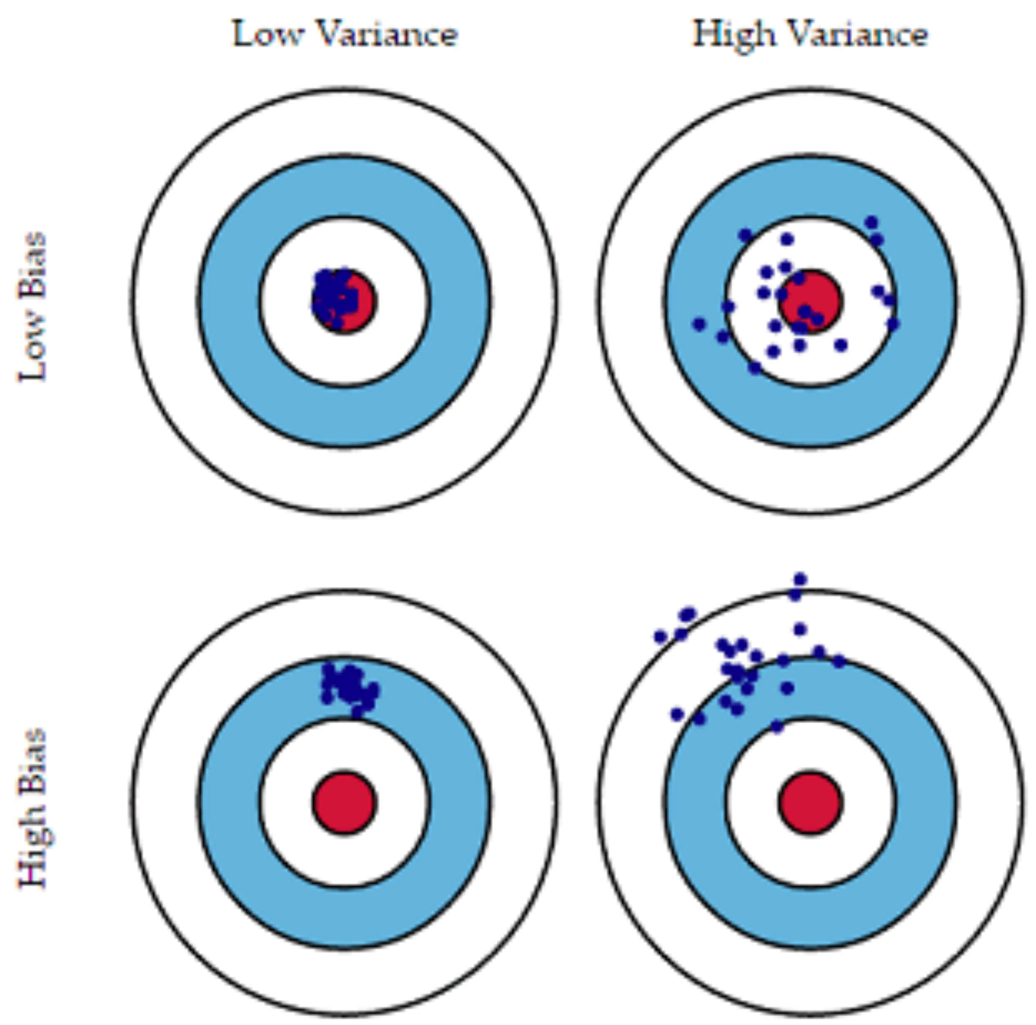

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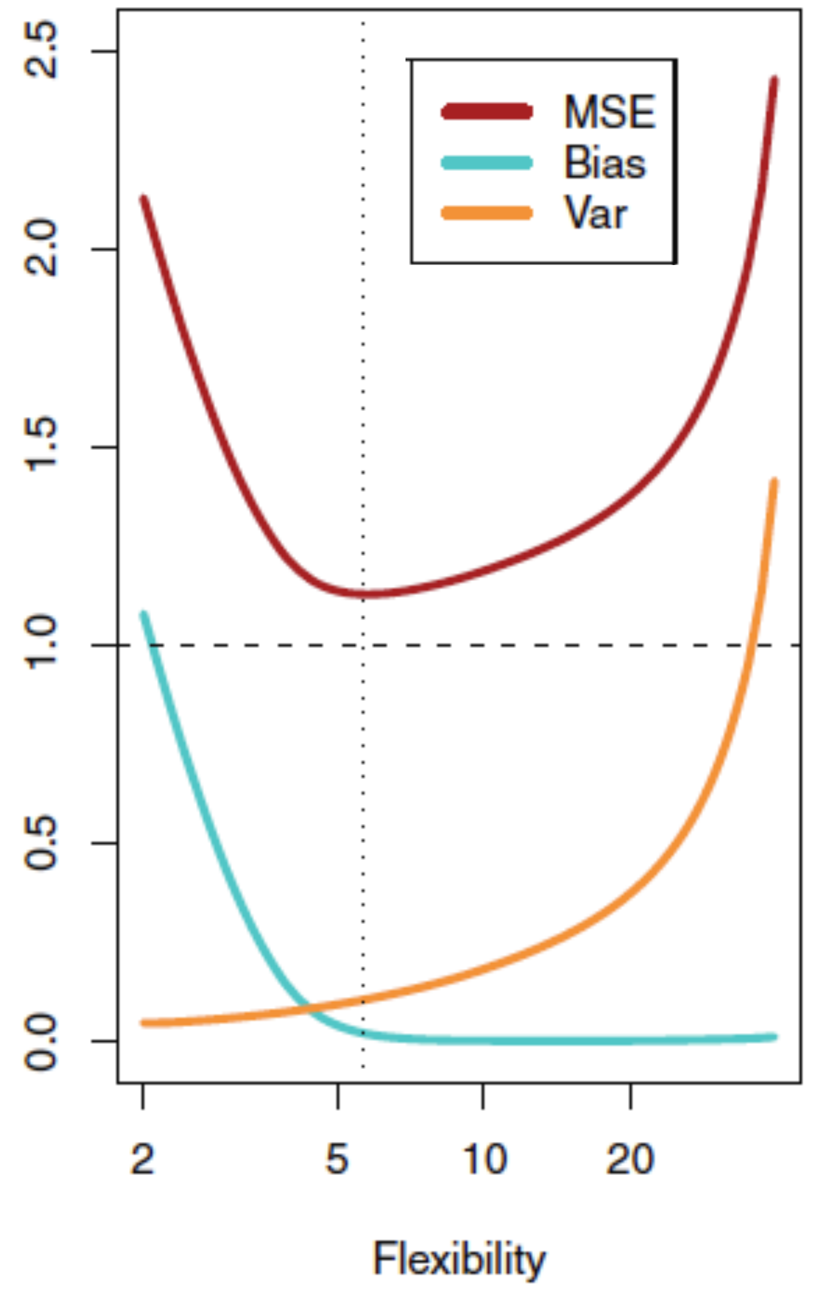

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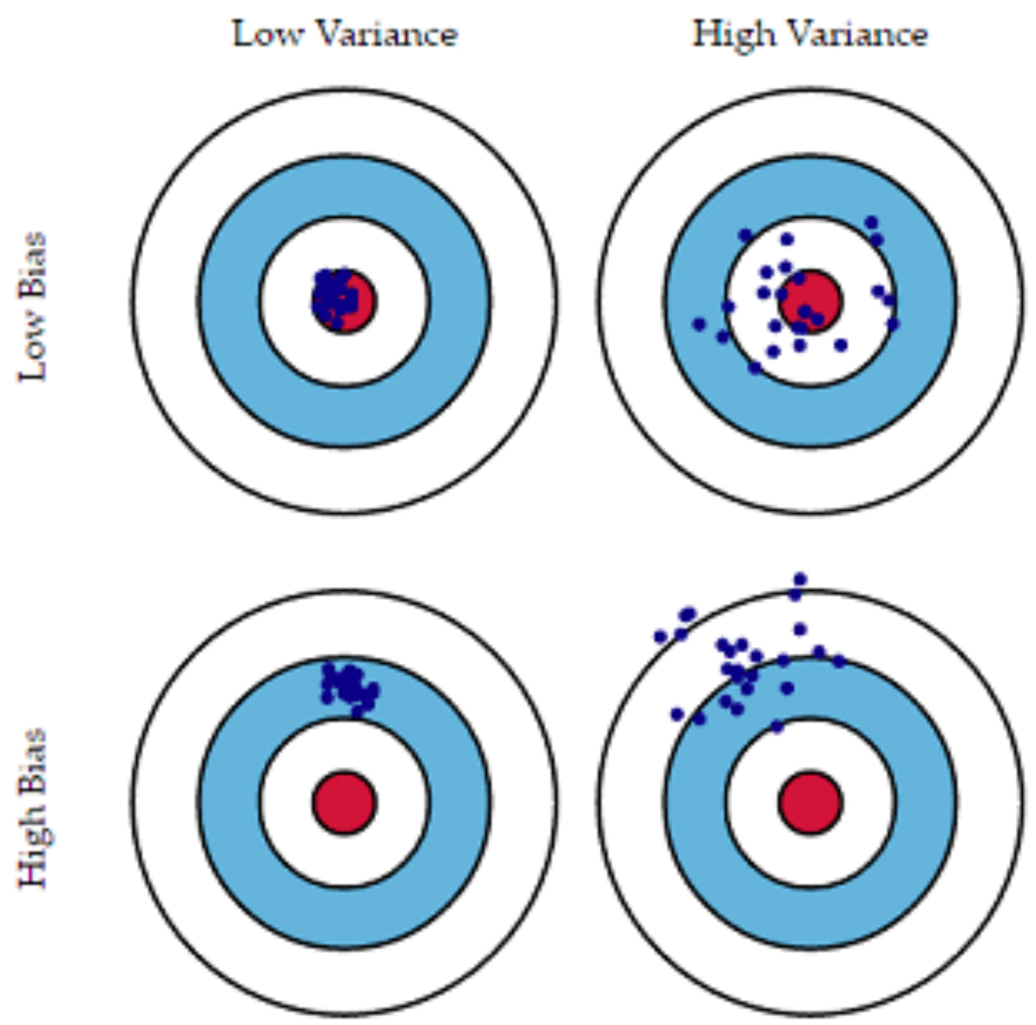

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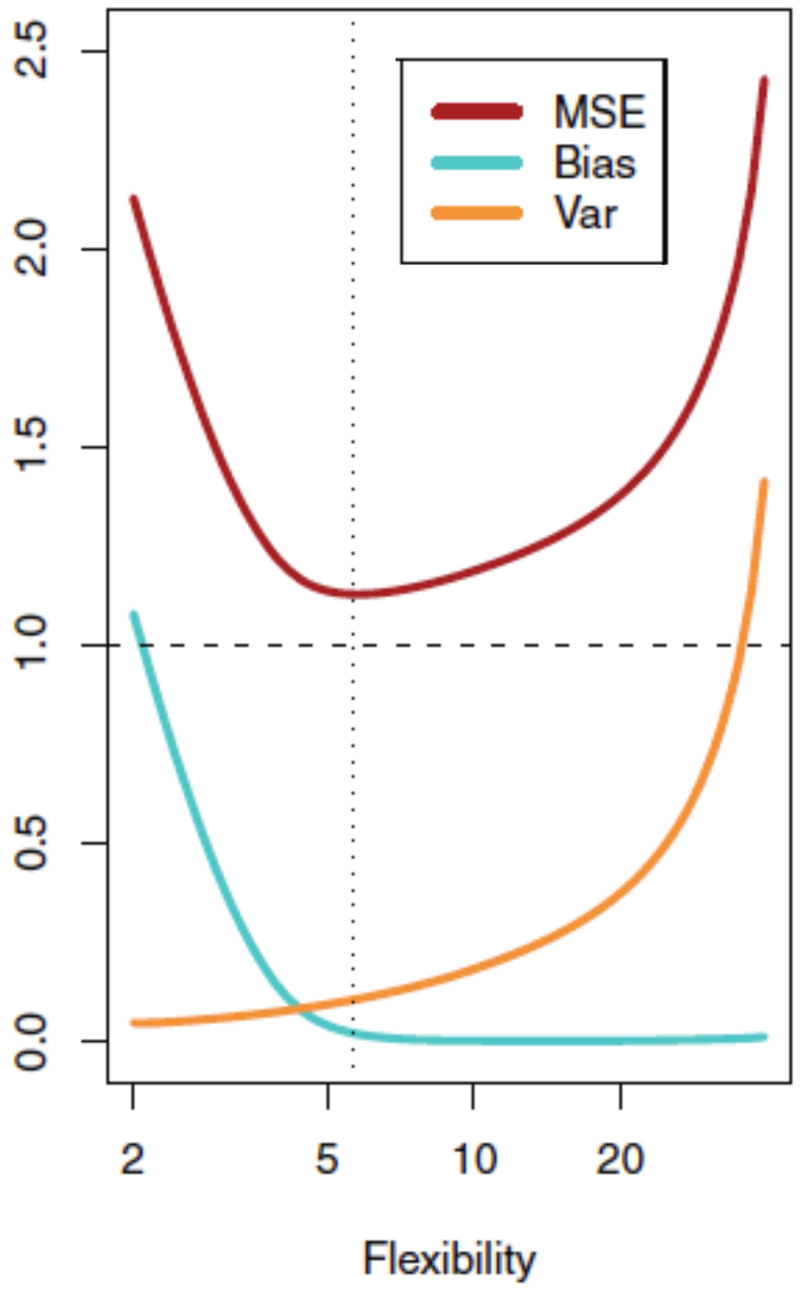

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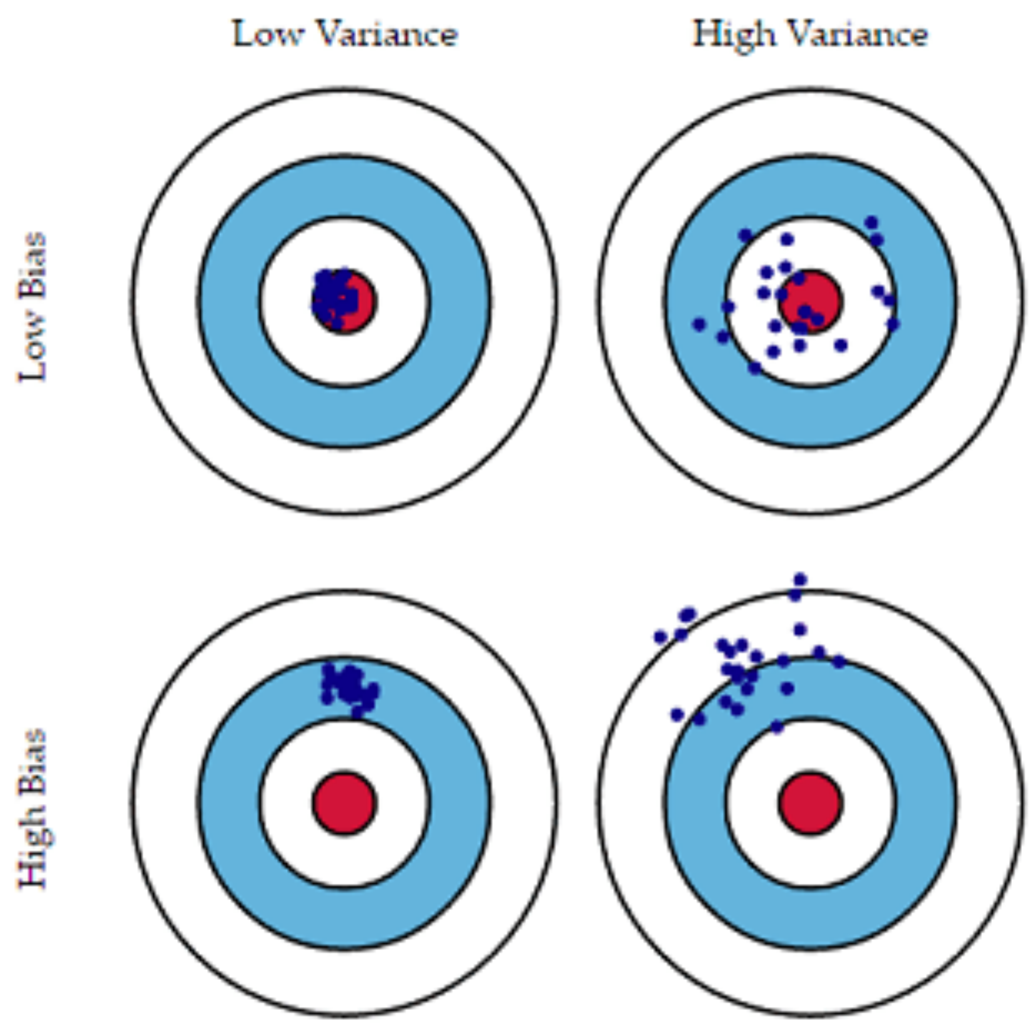
Lower noise or larger sample size means you can afford more complex model (think of deep learning).



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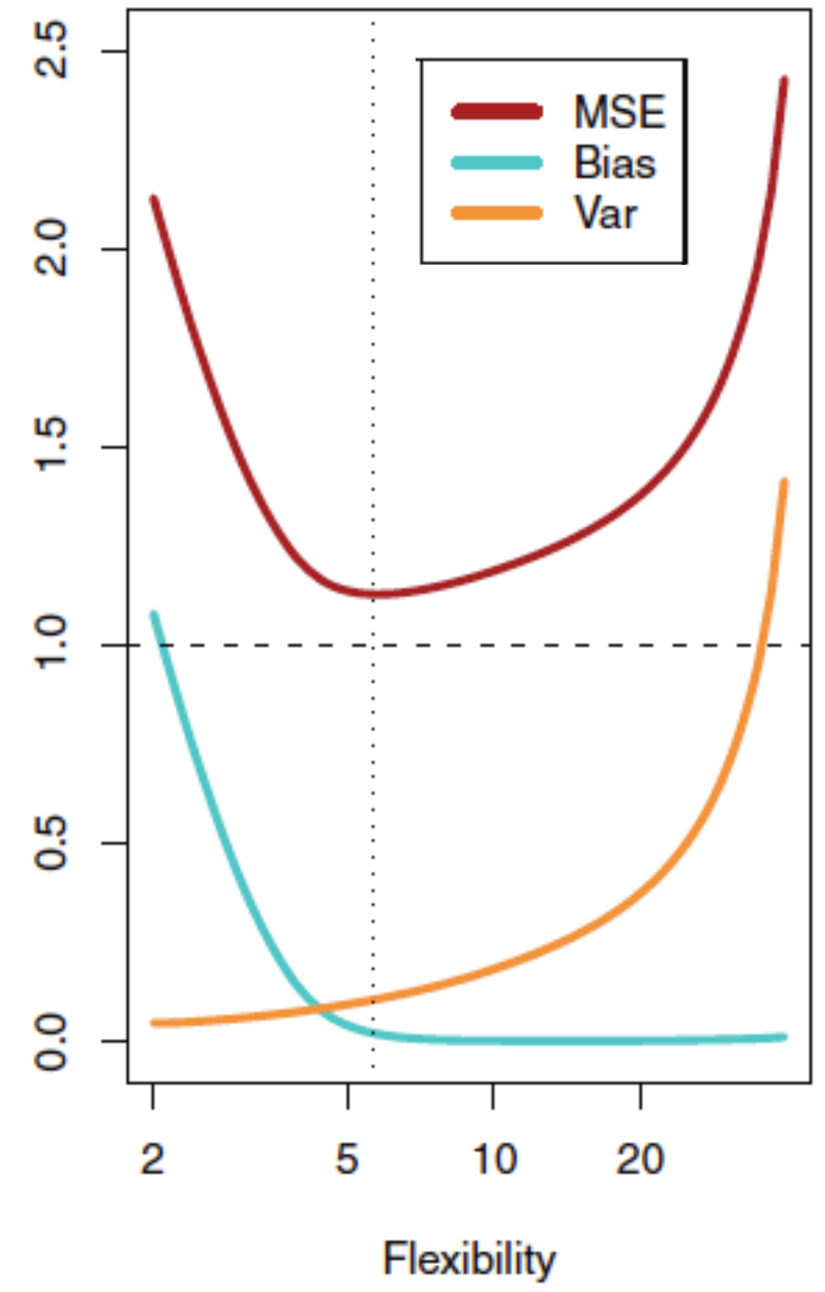

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- One-standard-error rule reflects preference for simpler models.

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- R is well suited for data science; lots of packages available to analyze data.

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- The most successful analyses couple statistical intuition and data intuition.
- Ultimate goal of data science is to create knowledge and/or make decisions; we must make conclusions relevant to the underlying real-world problem.

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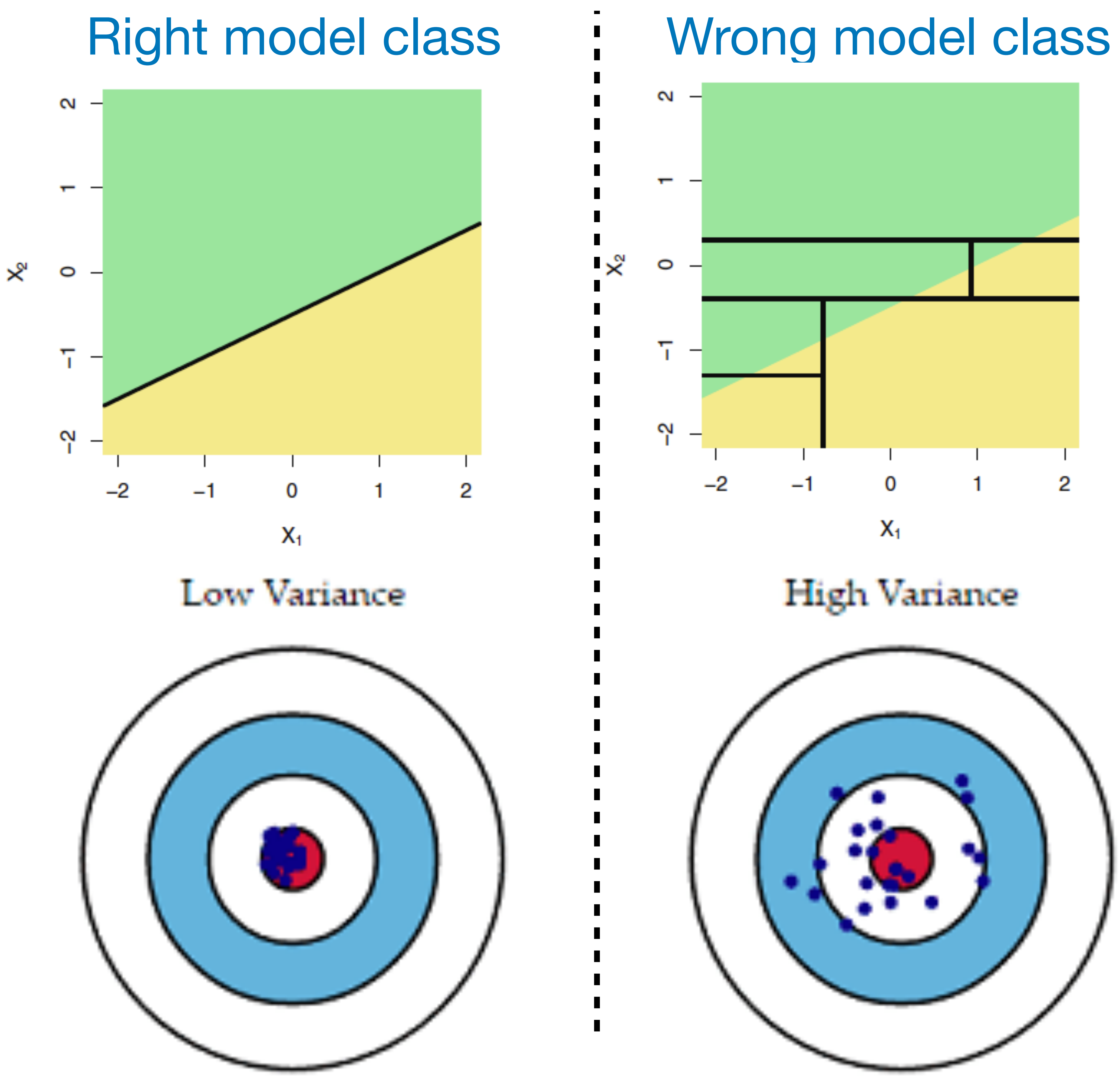
If true feature-response relationship matches model class our method “has in mind,” will take fewer parameters (less variance) to fit underlying trend (less bias).



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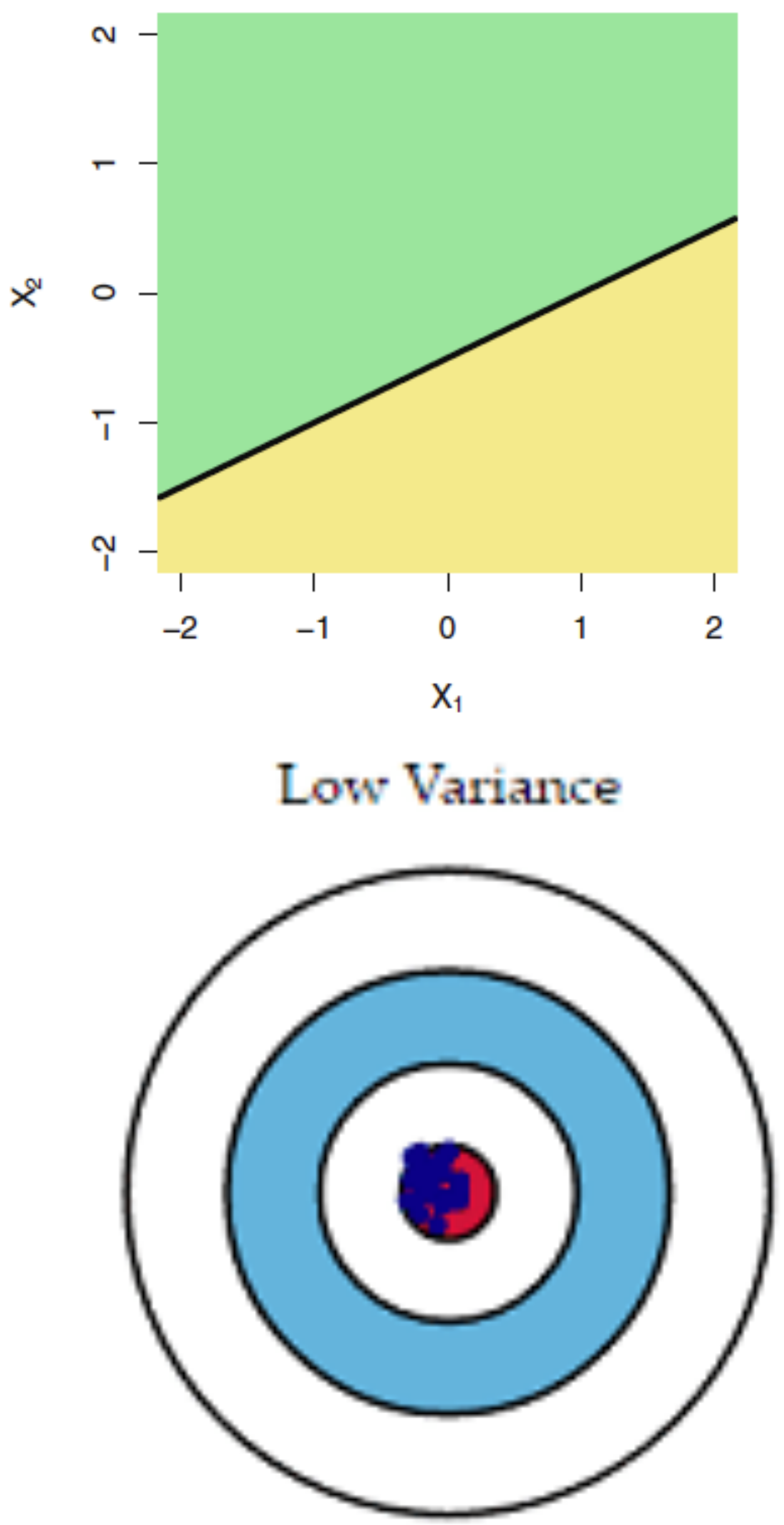
Moral of the story: It’s good to know several prediction methods. Seek out the ones whose underlying model class you think matches the true feature-response relationship.

Right model class



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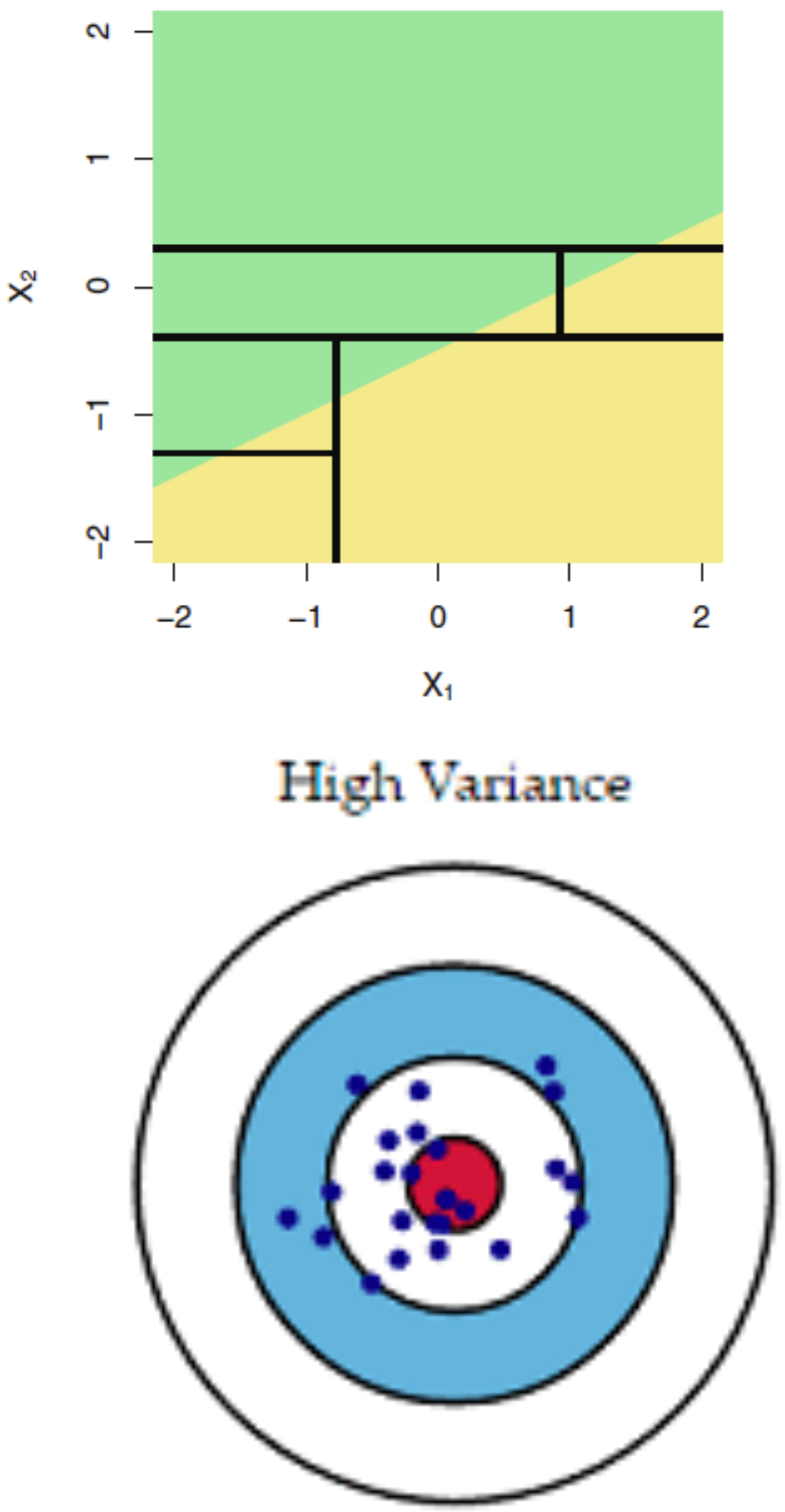

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Looking beyond STAT 4710

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- In the short term, AI will automate routine tasks, and serve as an increasingly capable assistant. In the medium-to-longer term, hard to predict!

Learning more about data mining, ML, and AI

	Computation	Theory	Artificial intelligence
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Advanced			

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Fairness: In what sense can a prediction rule be considered fair? How can we assure that our predictive rules live up to this standard?

Data science jobs

Data Scientist: The Sexiest Job of the 21st Century

Harvard Business Review

Meet the people who can coax treasure out of messy, unstructured data. by Thomas H. Davenport and D.J. Patil

From the Magazine (October 2012)

glassdoor

50 Best Jobs in America for 2022

	Job Title	Median Base Salary	Job Satisfaction	Job Openings
#1	Enterprise Architect	$144,997	4.1/5	14,021
#2	Full Stack Engineer	$101,794	4.3/5	11,252
#3	Data Scientist	$120,000	4.1/5	10,071
#4	Devops Engineer	$120,095	4.2/5	8,548
#5	Strategy Manager	$140,000	4.2/5	6,977

What does a Data Scientist do?

Data scientists utilize their analytical, statistical, and programming skills to collect, analyze, and interpret large data sets. They then use this information to develop data-driven solutions to difficult business challenges. Data scientists commonly have a bachelor's degree in statistics, math, computer science, or economics. Data scientists have a wide range of technical...

Read More

Average Years of Experience

- 0 - 1: 8%
- 2 - 4: 80%
- 5 - 7: 6%
- 8+: 6%

Common Skill Sets

- Machine Learning
- Python
- Hadoop SPARK
- SQL
- Statistics
- Natural Language Processing
- Algorithms
- Programming Languages

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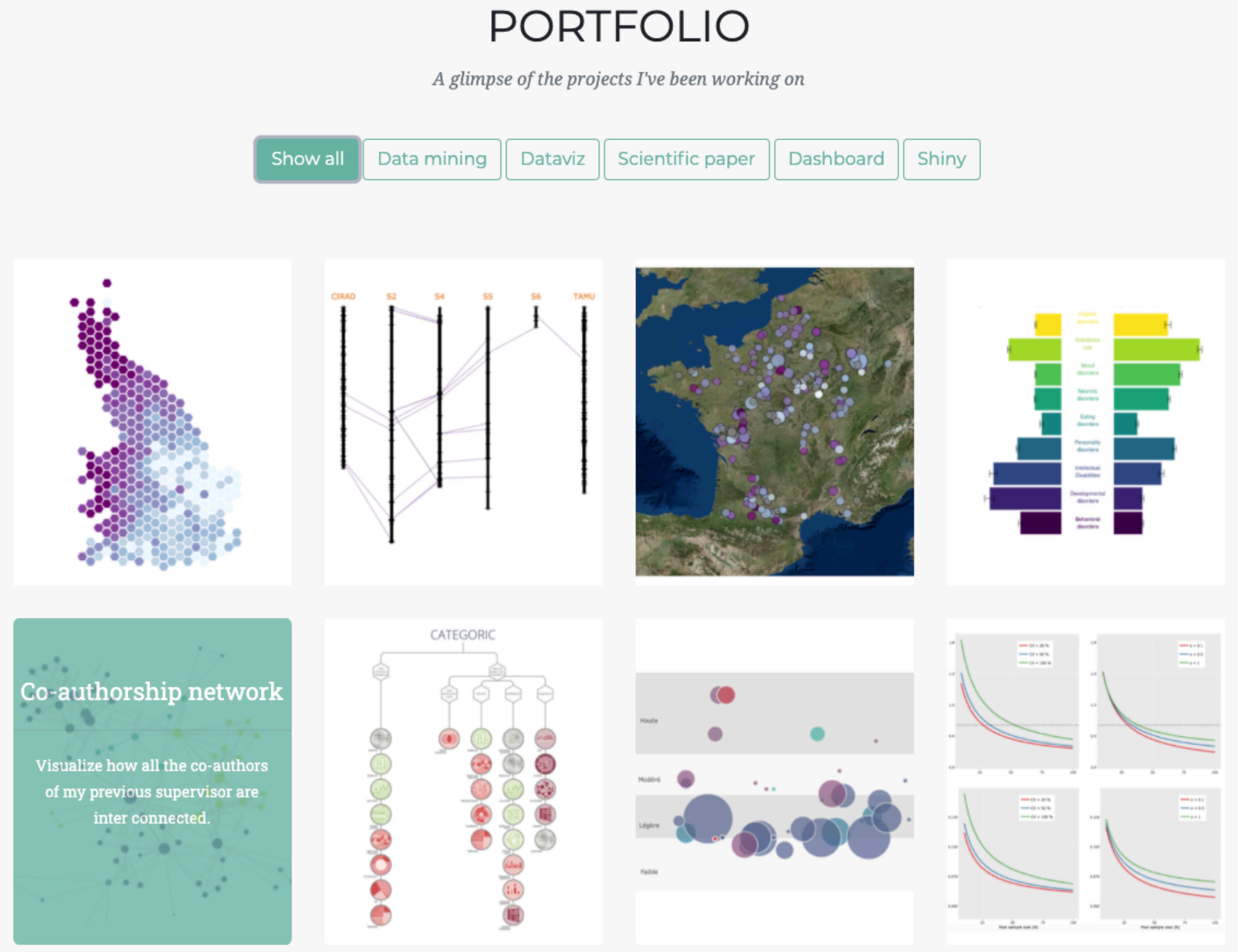

https://www.yan-holtz.com/

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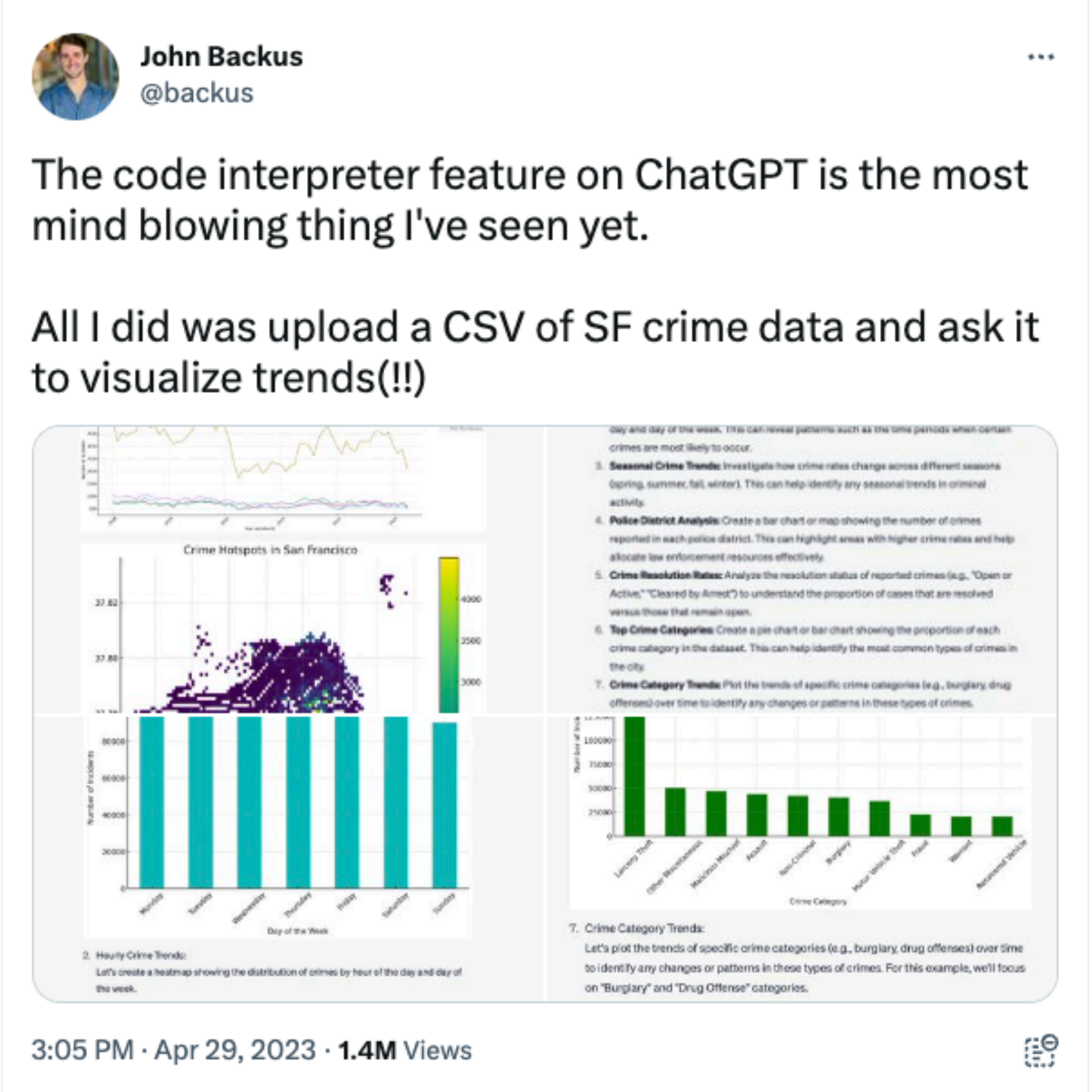

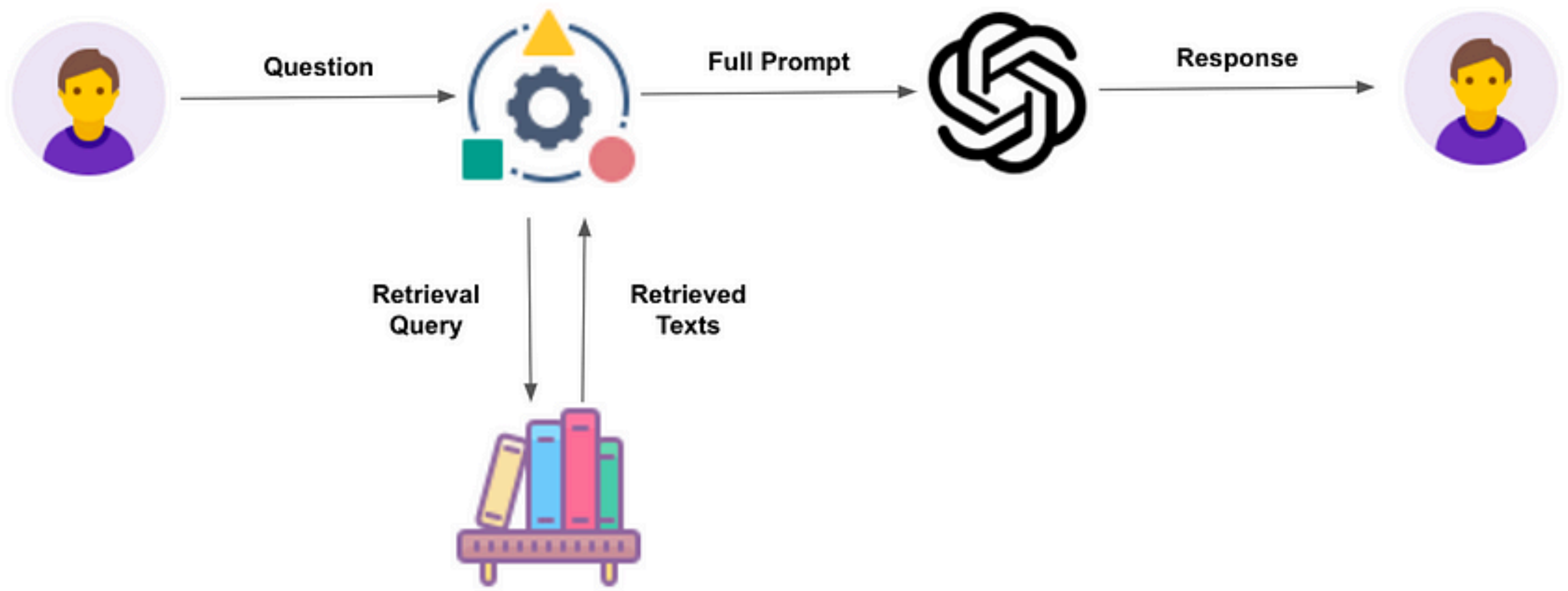

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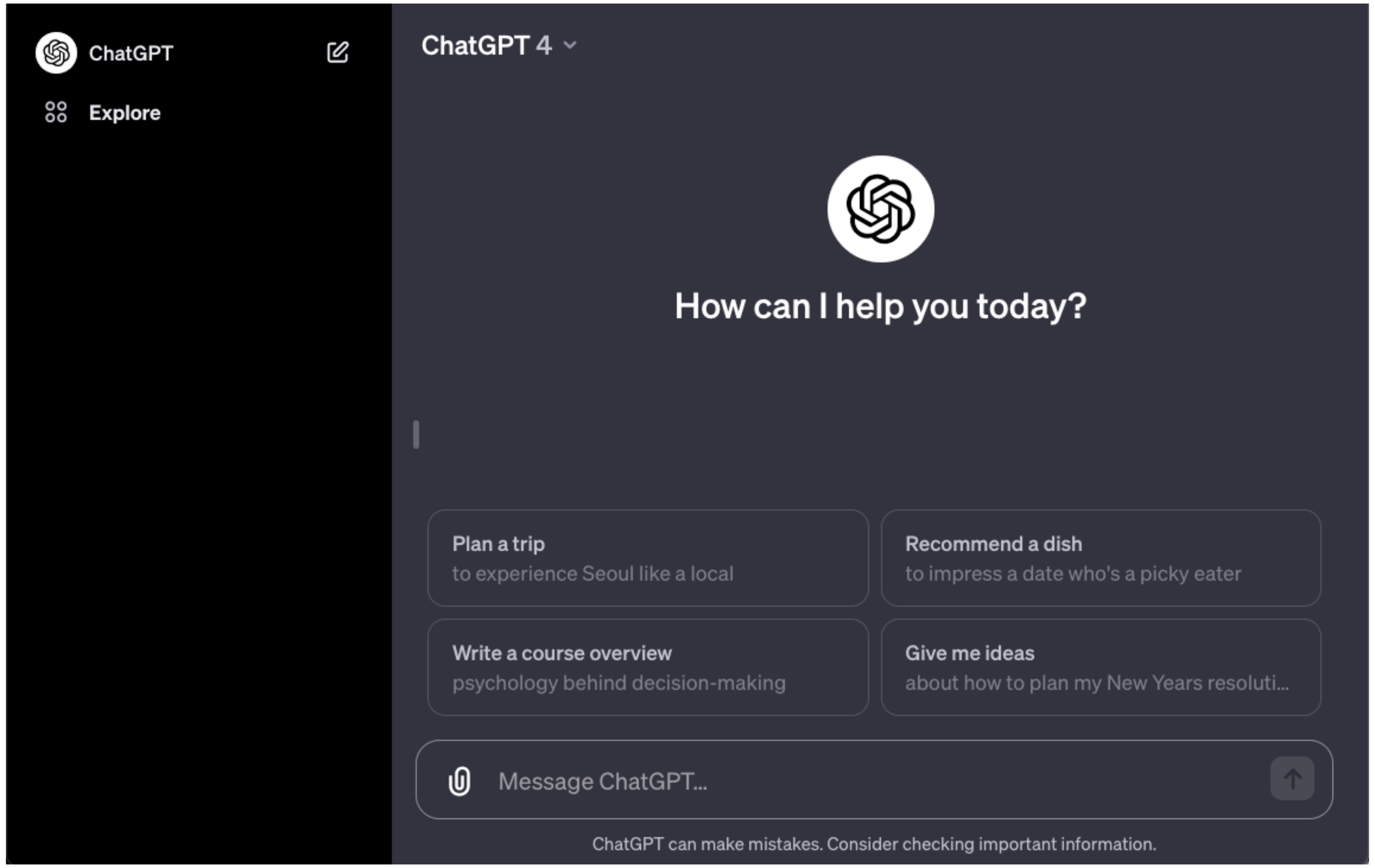

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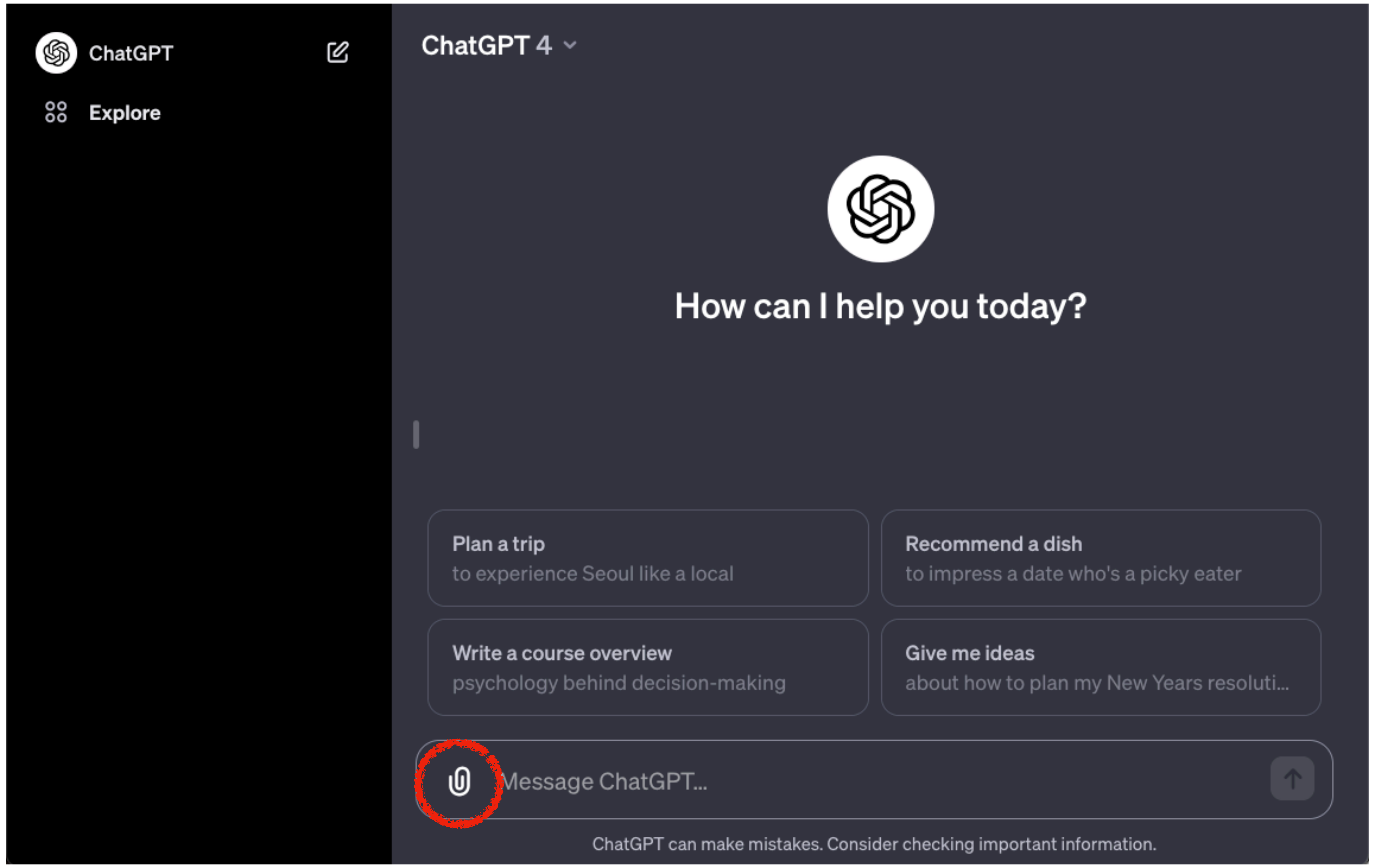

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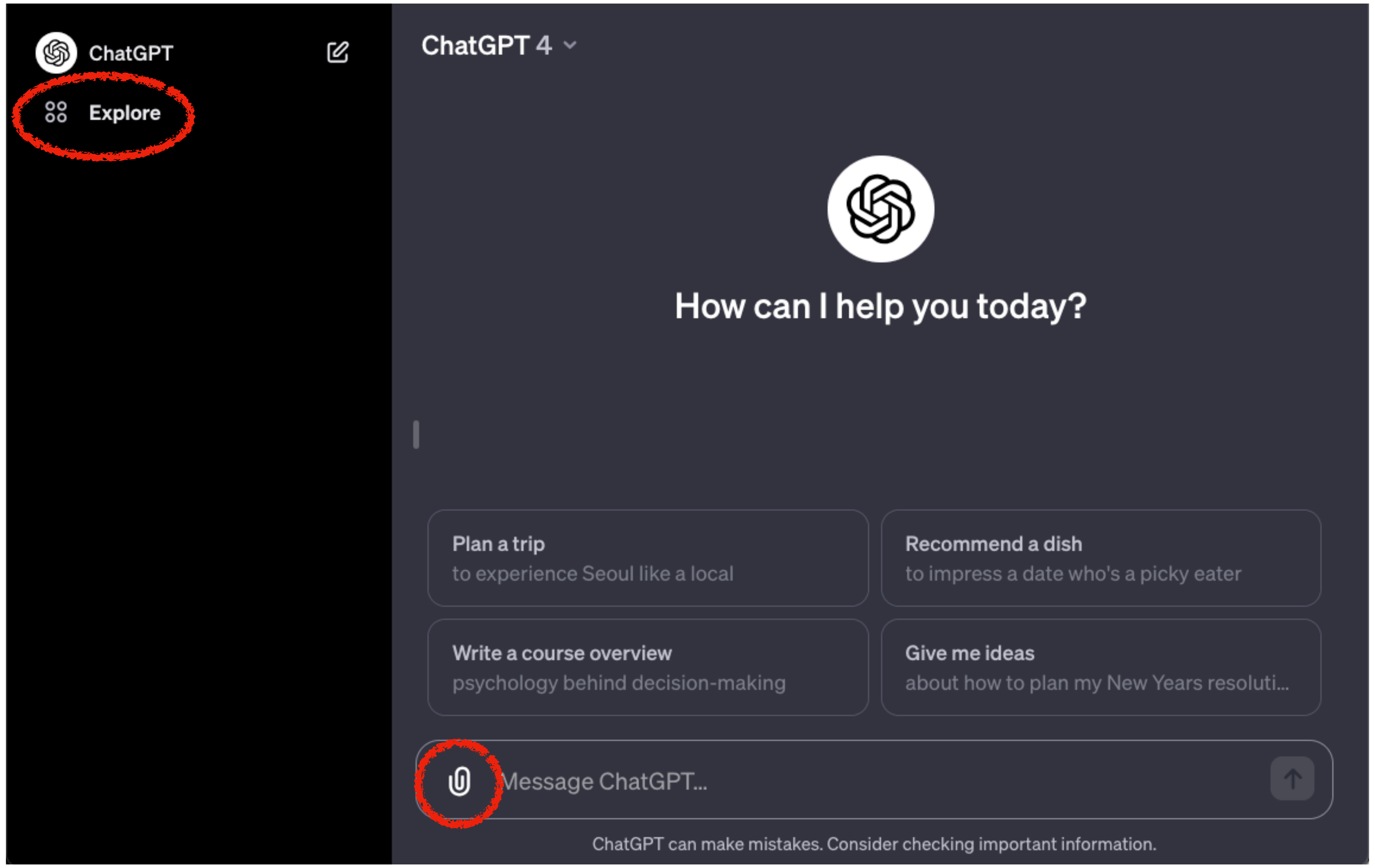

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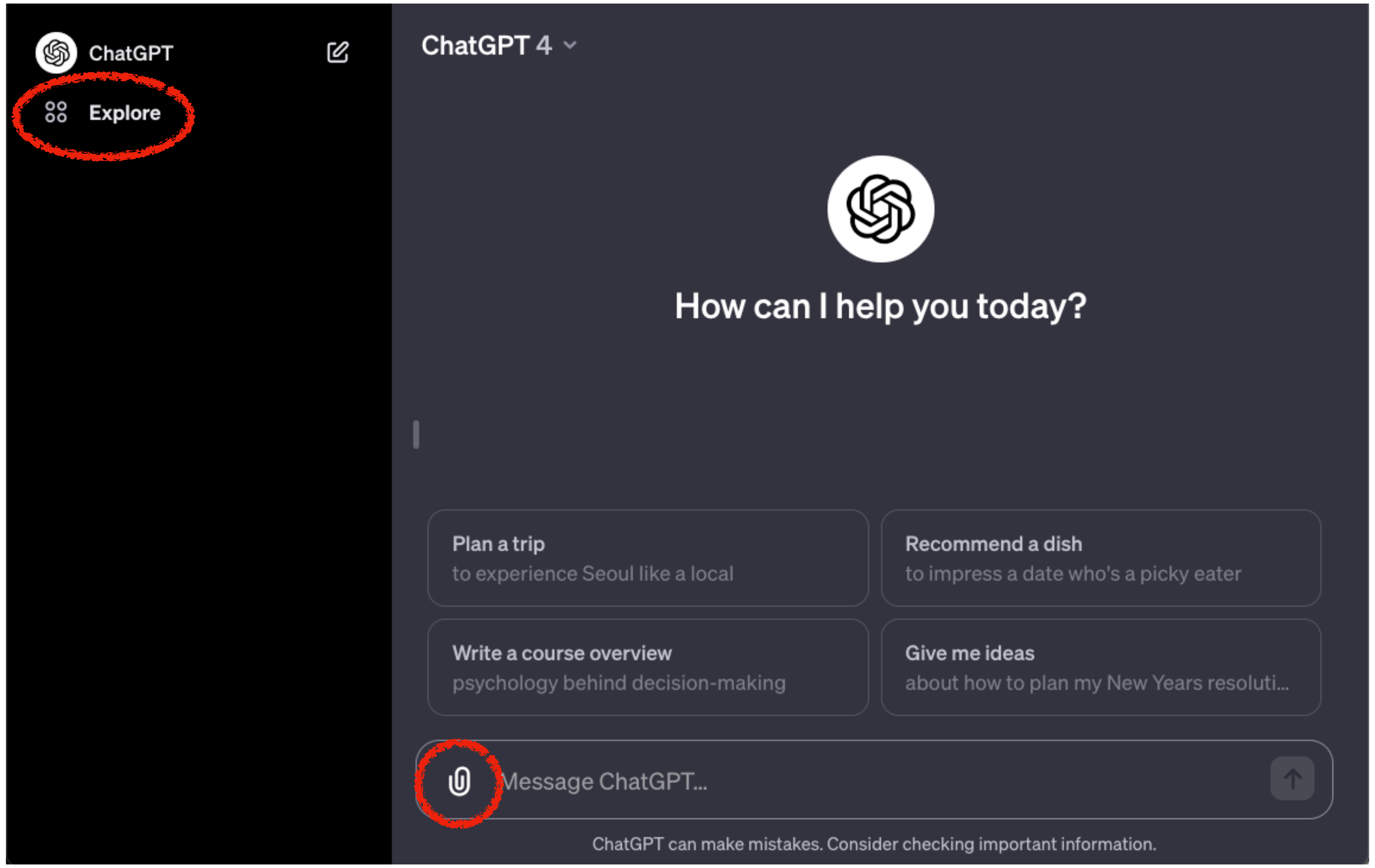

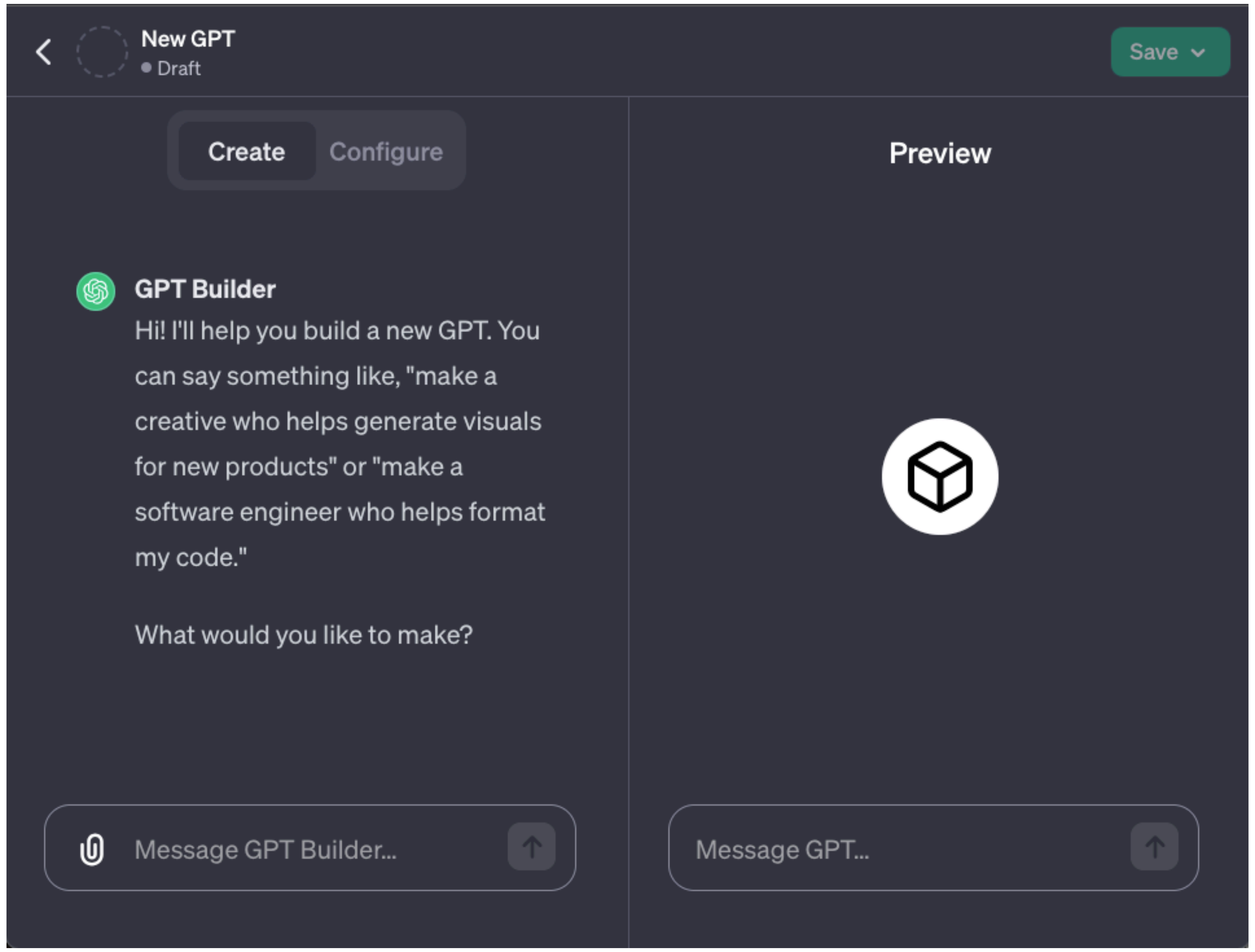

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See OpenAI developer platform, Hugging Face, and LangChain.