

# Lecture 000

Why are we here?

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Admin

# Admin

## In-class today

- **Course website:** <https://github.com/edrubin/EC524W20/>
- [Syllabus](#) (on website)

## TODO list

- [Assignment](#) (from Tuesday) due Thursday
- Readings for next time:
  - ISL Ch1–Ch2
  - [Prediction Policy Problems](#) by Kleinberg *et al.* (2015)

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meaning we want an unbiased (consistent) and precise estimate  $\hat{\beta}$ .

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With **prediction**, we shift our focus to accurately estimating outcomes.

In other words, how can we best construct  $\hat{Y}_i$ ?

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... so?

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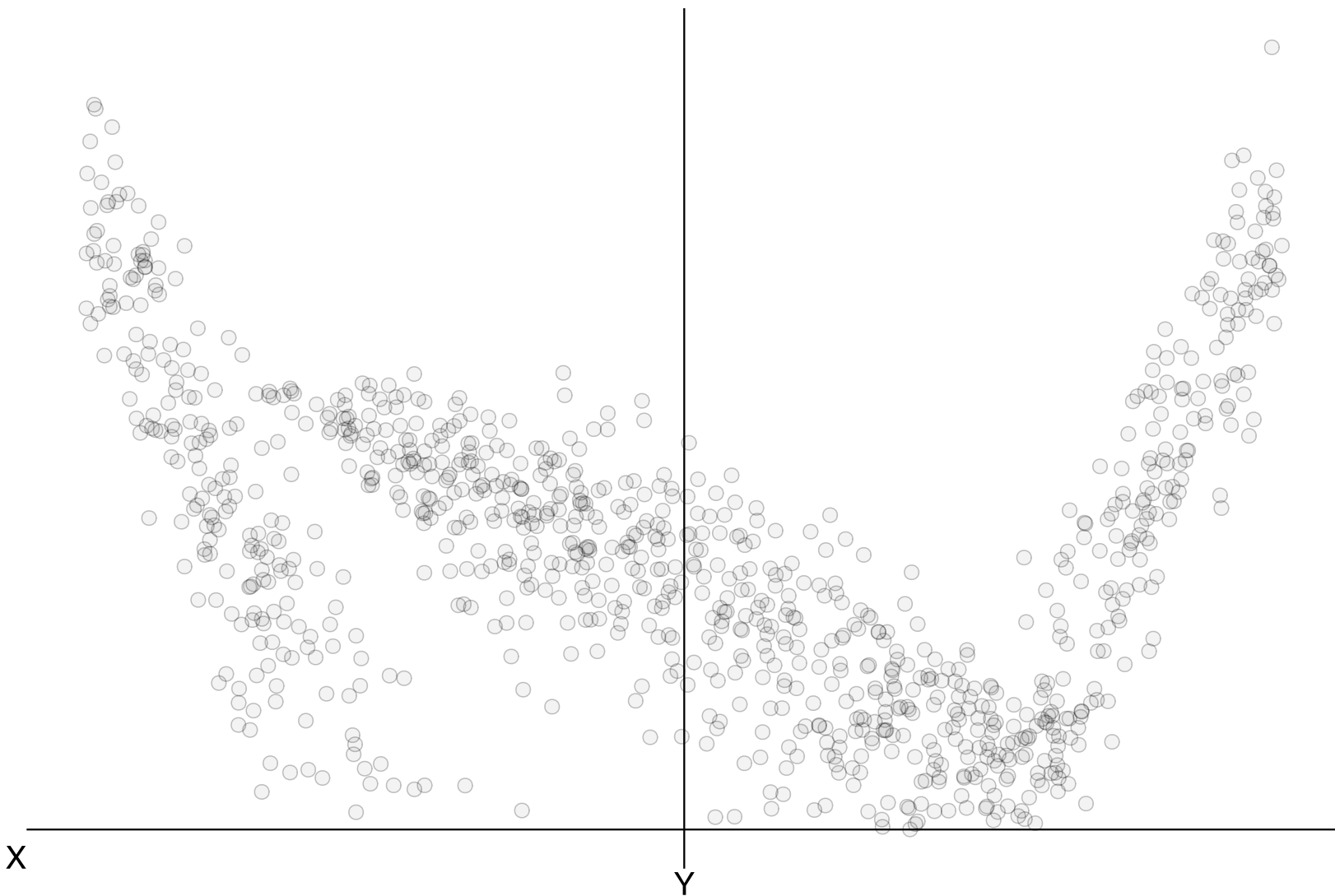
**Q** Can't we just use the same methods (*i.e.*, OLS)?

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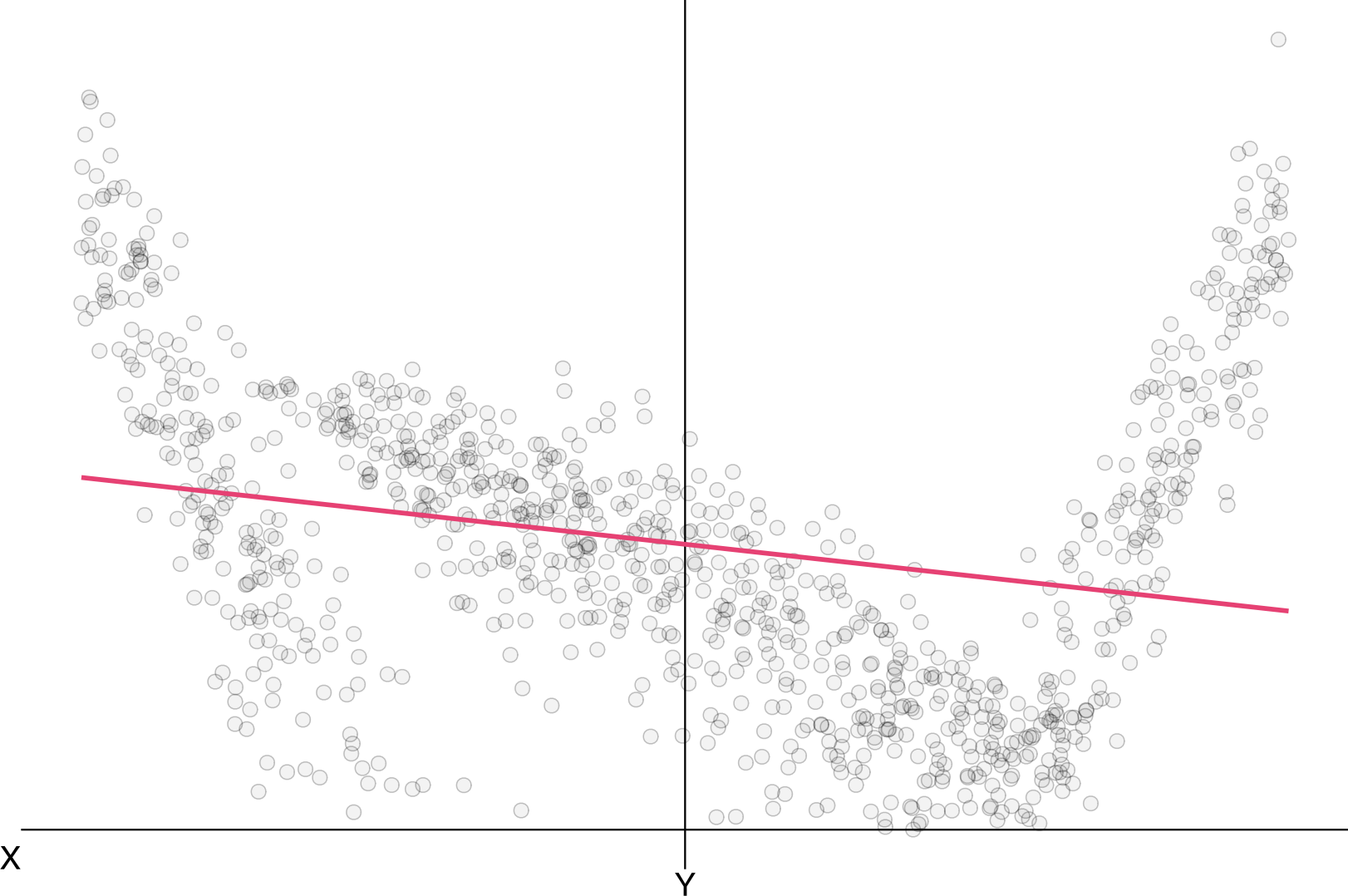
*Recall* Least-squares regression is a great **linear** estimator.

Data data be tricky<sup>†</sup>—as can understanding many relationships.

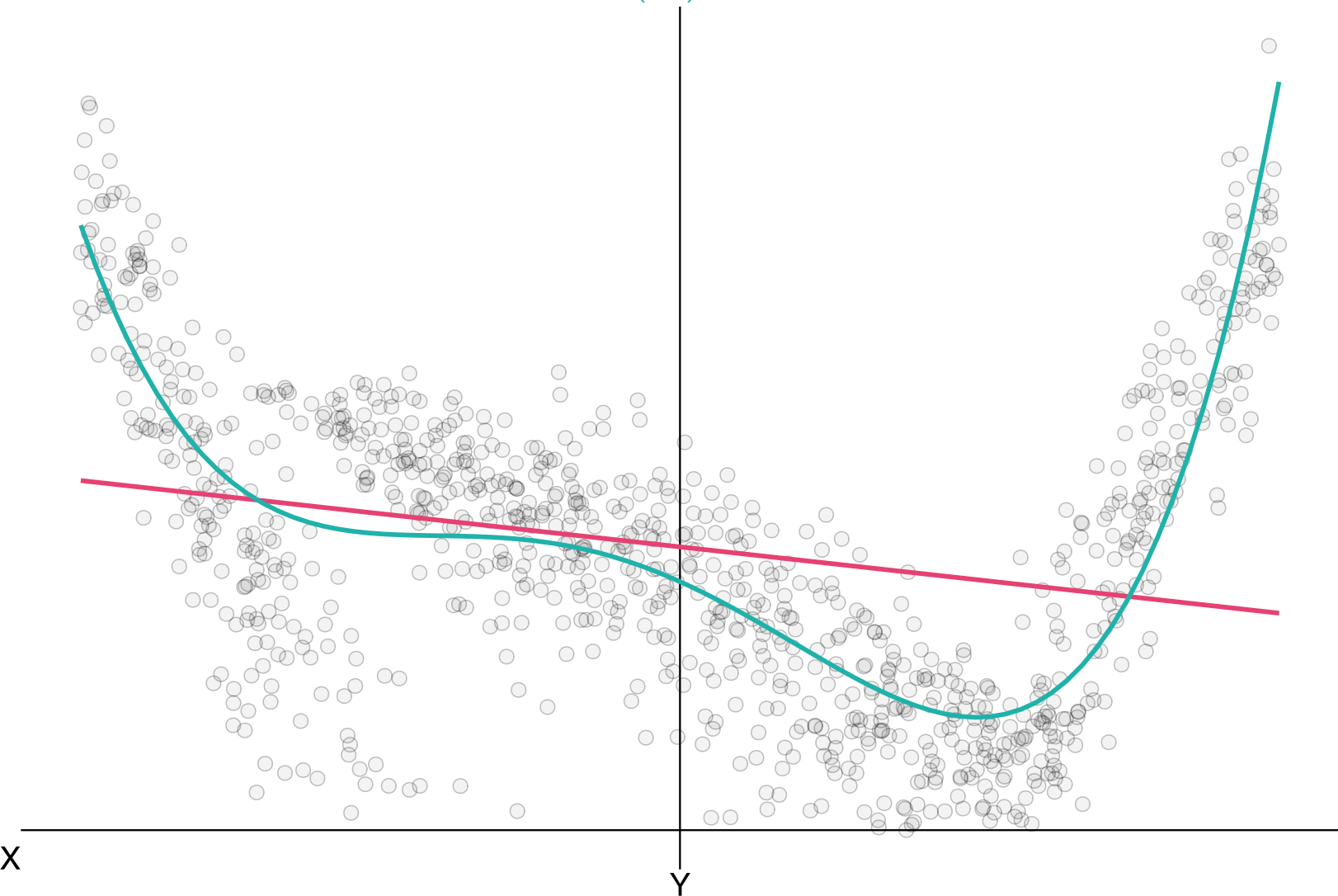
<sup>†</sup> "Tricky" might mean nonlinear... or many other things...



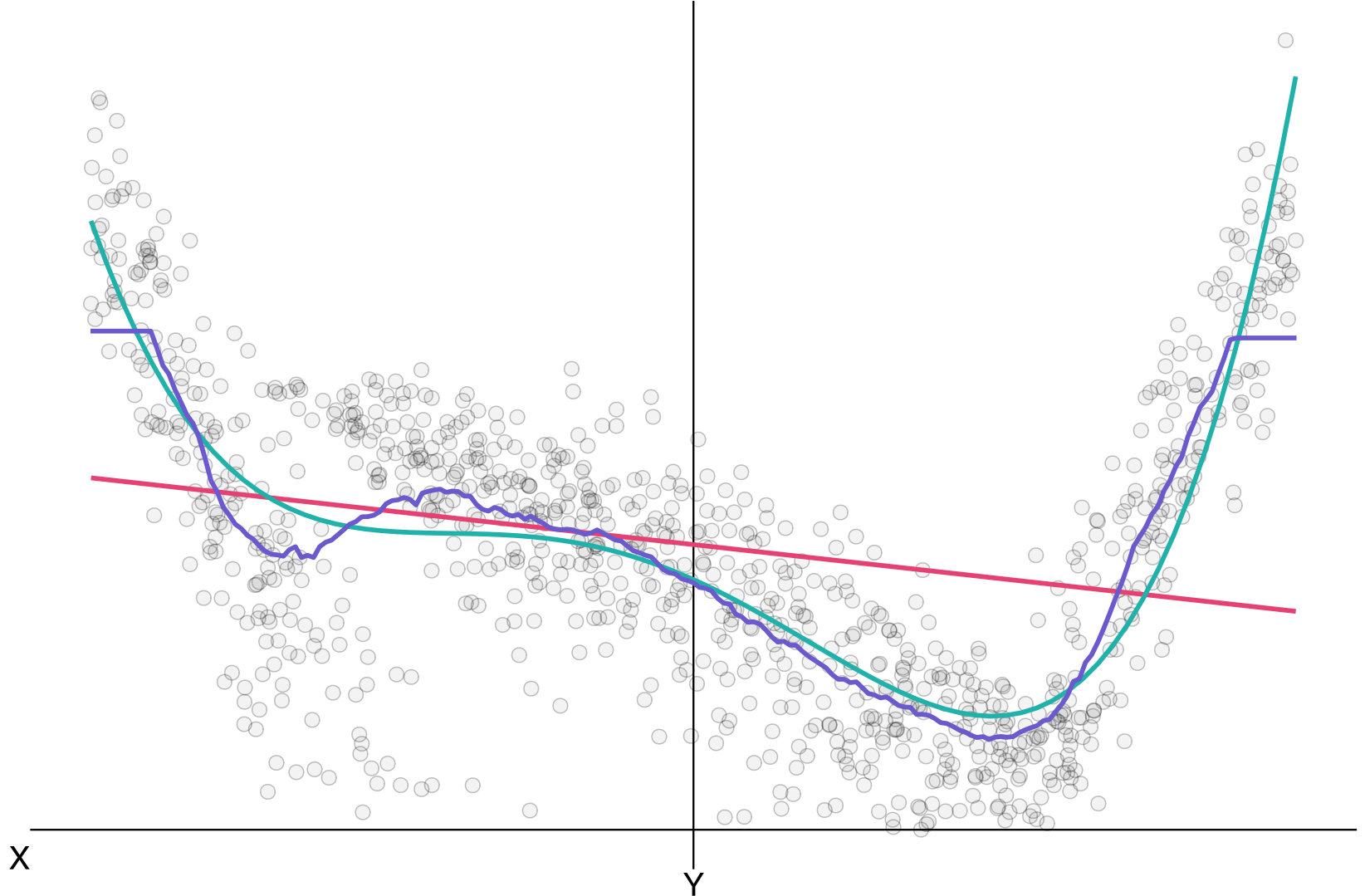
Linear regression



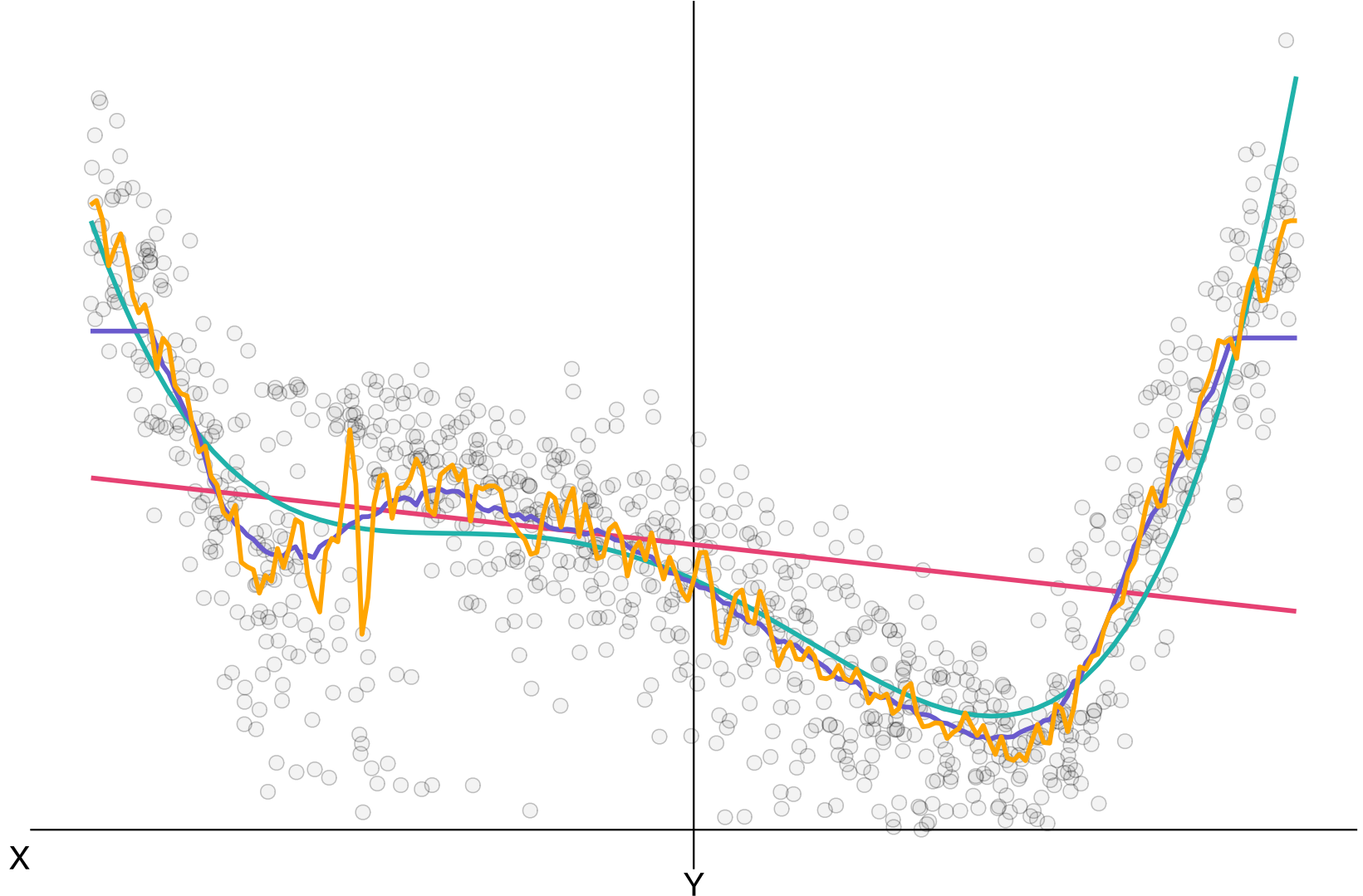
Linear regression, linear regression ( $x^4$ )



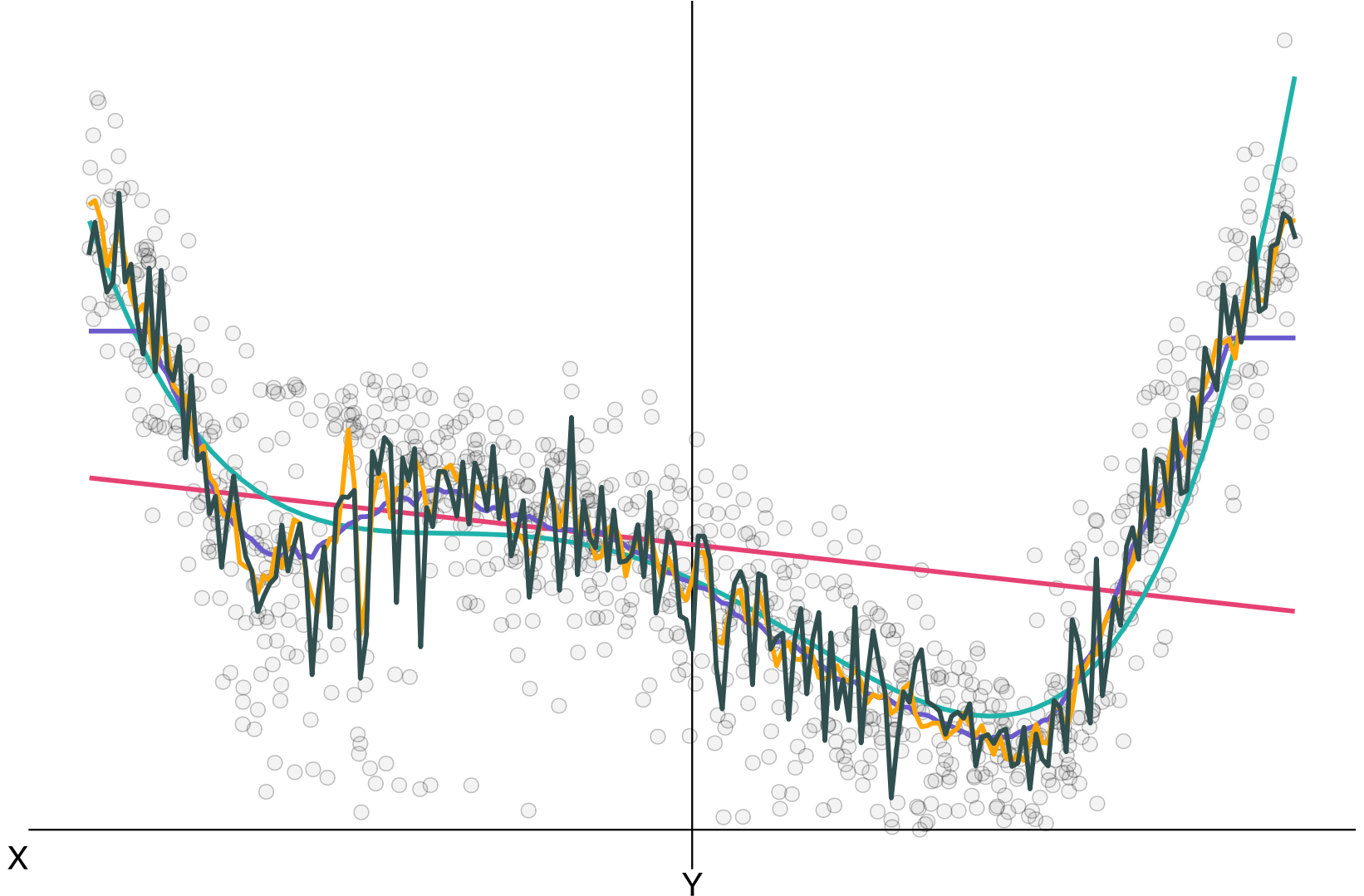
Linear regression, linear regression ( $x^4$ ), KNN (100)



Linear regression, linear regression ( $x^4$ ), KNN (100), KNN (10)



Linear regression, linear regression ( $x^4$ ), KNN (100), KNN (10), random forest



*Note* That example was only in one dimension...

# What's the goal?

## Tradeoffs

In prediction, we constantly face many tradeoffs, *e.g.*,

- **flexibility** and **parametric structure** (and interpretability)
- performance in **training** and **test** samples
- **variance** and **bias**

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Many machine-learning (ML) techniques/algorithms are crafted to optimize with these tradeoffs, but the practitioner (you) still needs to be careful.

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## **Multi-class** classification problems

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**Text analysis** and **image recognition**

- Comb through sentences (pixels) to glean insights from relationships
- *E.g.*, detect sentiments in tweets or roof-top solar in satellite imagery

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## **Multi-class** classification problems

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## **Unsupervised learning**

- You don't know groupings, but you think there are relevant groups
- *E.g.*, classify spatial data into groups



**Stanford University (Stanford, CA ) researchers have developed a deep-learning algorithm that can evaluate chest X-ray images for signs of disease at a level exceeding practicing radiologists.**



Parking Lot Vehicle Detection Using  
Deep Learning

THE  
NEW YORKER

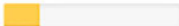
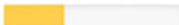
A REPORTER AT LARGE OCTOBER 14, 2019 ISSUE

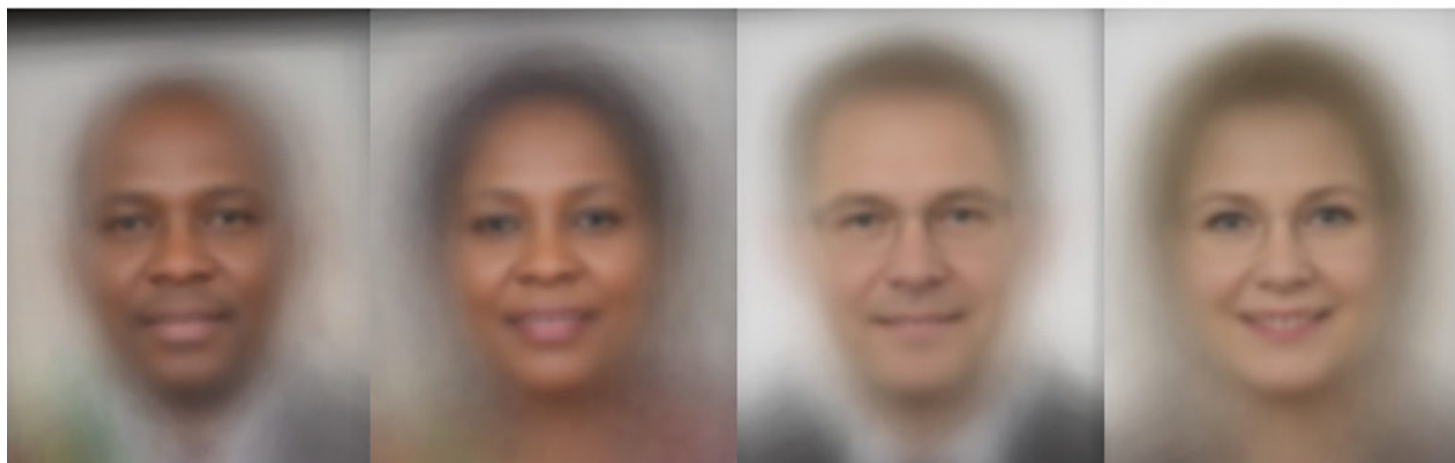
# The Next Word |

*Where will predictive text take us?*

Text by John Seabrook



| Gender Classifier                                                                           | Darker Male                                                                                | Darker Female                                                                              | Lighter Male                                                                                | Lighter Female                                                                               | Largest Gap                                                                                  |
|---------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|
|  Microsoft | 94.0%<br> | 79.2%<br> | 100%<br>  | 98.3%<br> | 20.8%<br> |
|  FACE++    | 99.3%<br> | 65.5%<br> | 99.2%<br> | 94.0%<br> | 33.8%<br> |
|  IBM       | 88.0%<br> | 65.3%<br> | 99.7%<br> | 92.9%<br> | 34.4%<br> |



Q What have you learned/noticed in your first project?

*Next time* Start formal building blocks of prediction.

# Sources

Sources (articles) of images

- Deep learning and radiology
- Parking lot detection
- *New Yorker* writing
- Gender Shades

# Table of contents

## Admin

- Today and upcoming

## What's the goal?

- What's difference?
- Graphical example
- Tradeoffs
- More goals
- Examples

## Other

- Image sources