

# Lecture 000

Why are we here?

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09 January 2020

# Admin

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

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

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... so?

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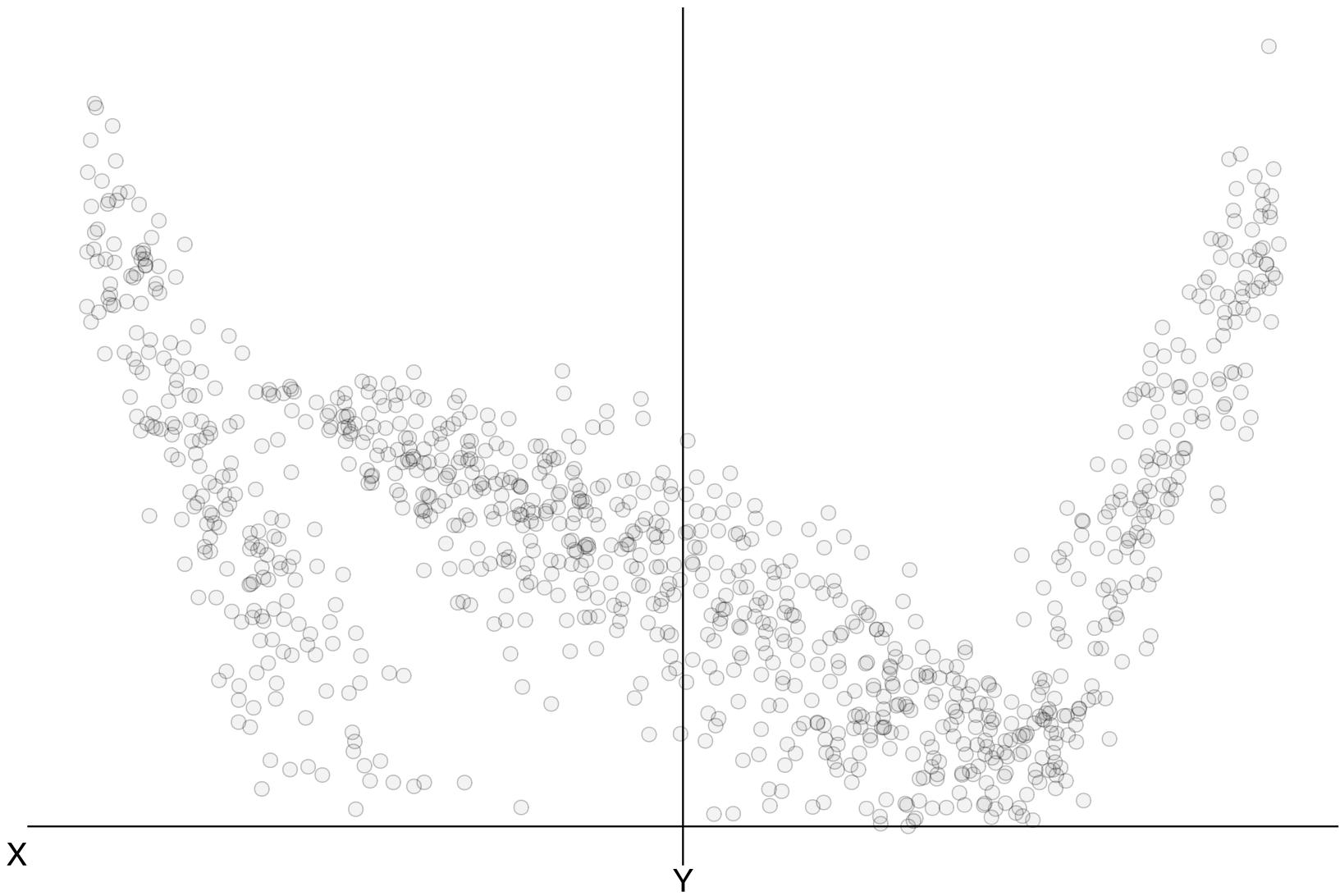
**Q** Can't we just use the same methods (*i.e.*, OLS)?

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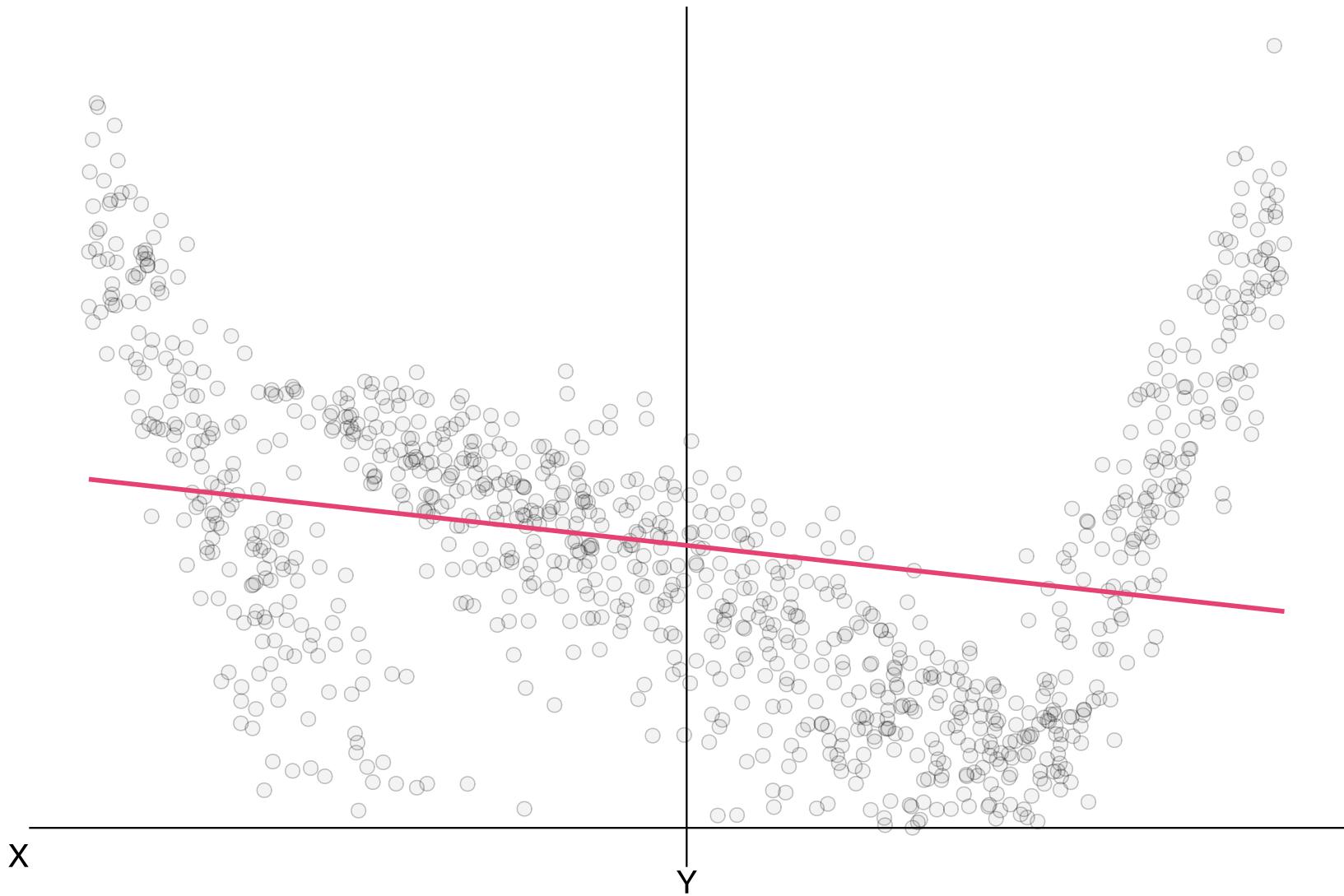
*Recall* Least-squares regression is a great **linear** estimator.

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

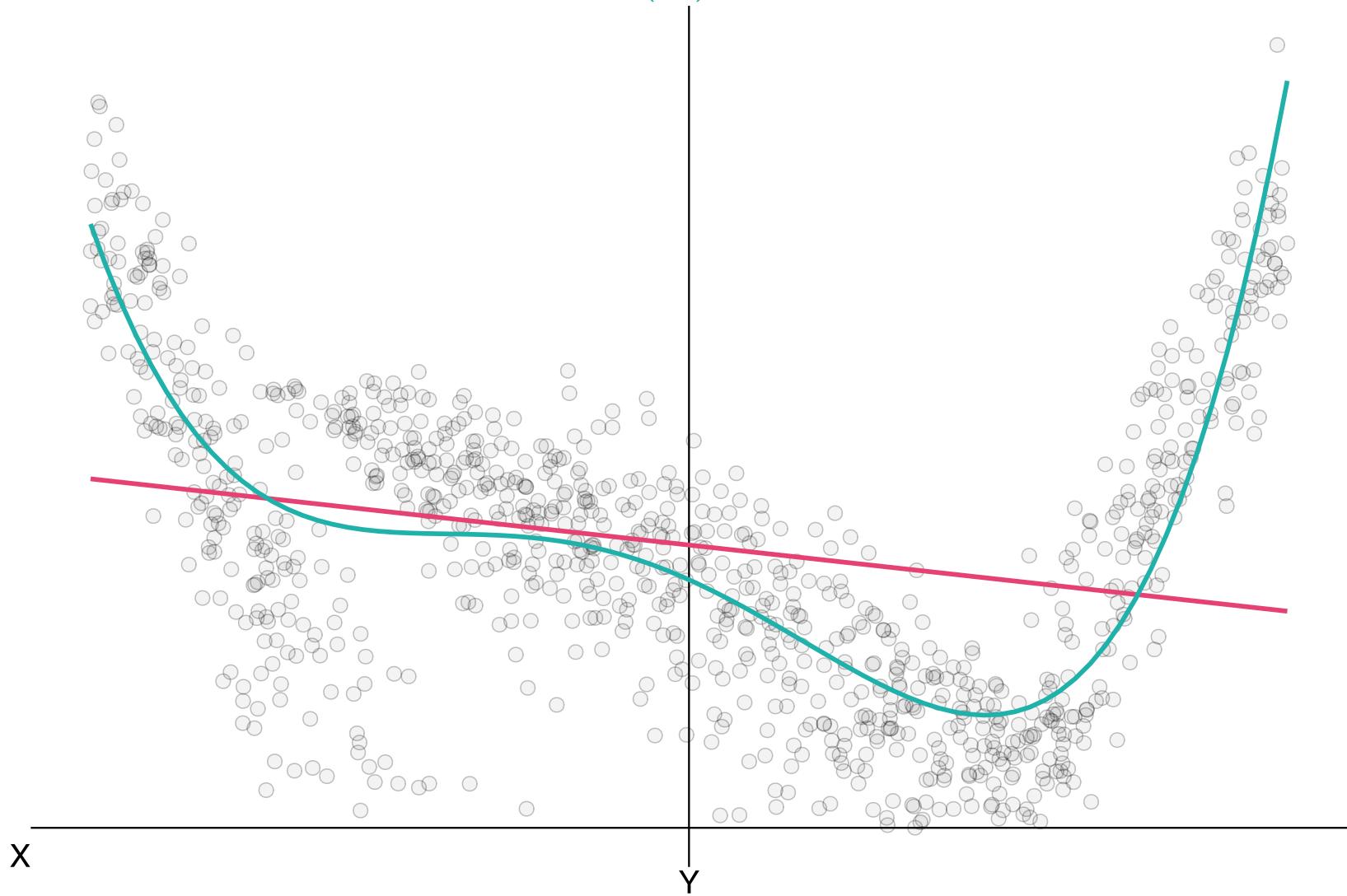
<sup>†</sup> "Tricky" might mean nonlinear... or many other things...



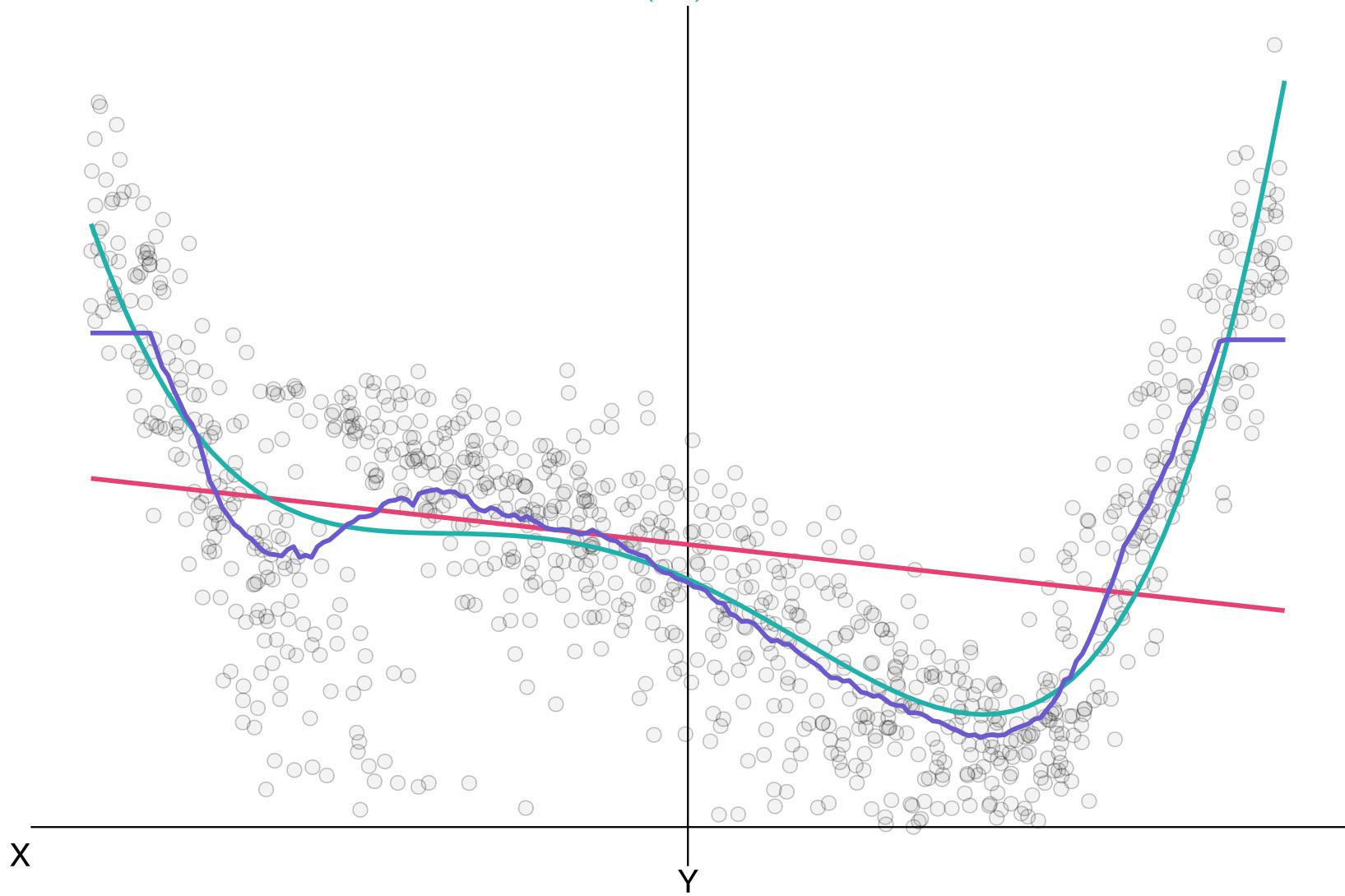
## Linear regression



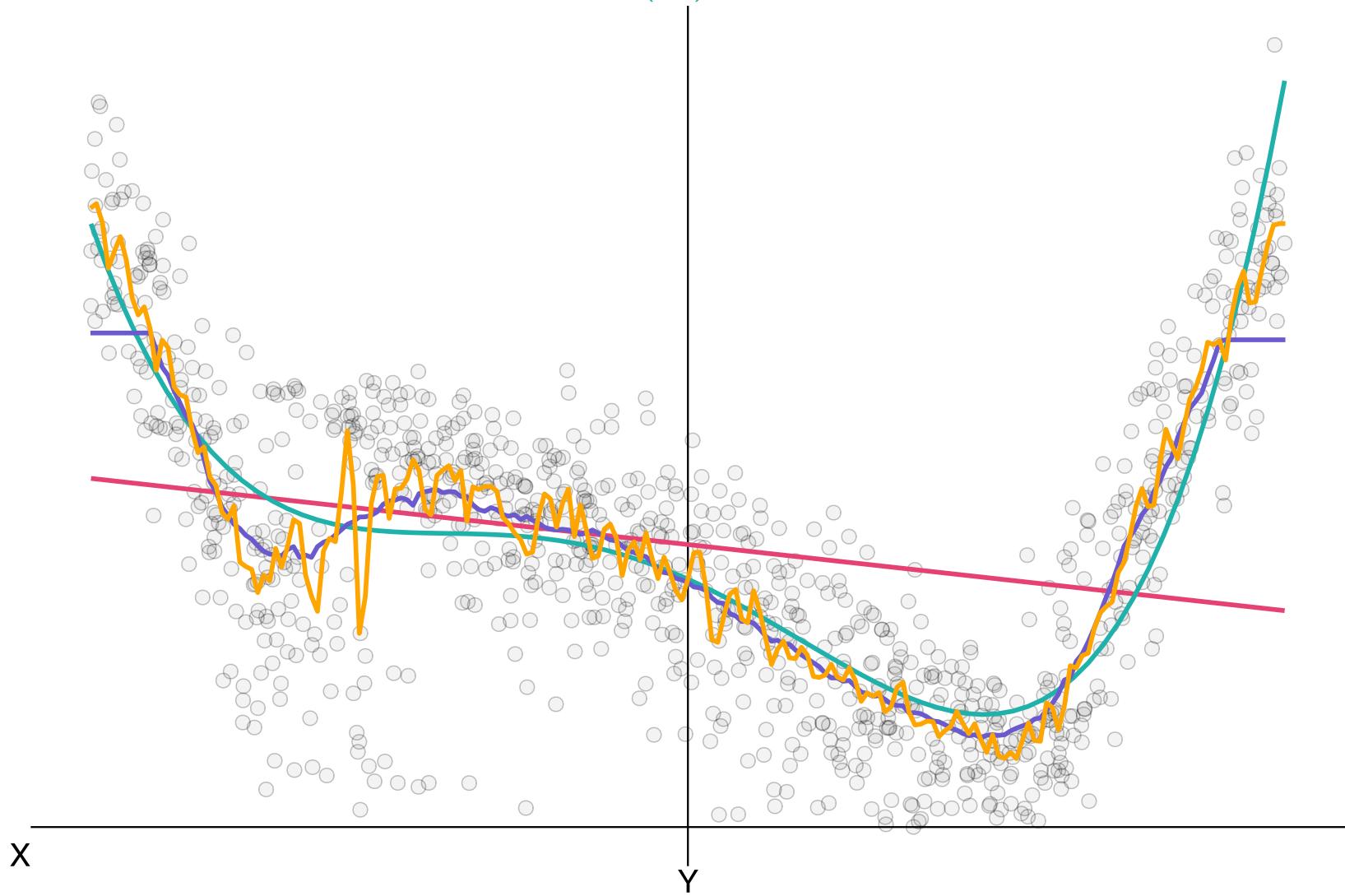
## Linear regression, linear regression ( $x^4$ )



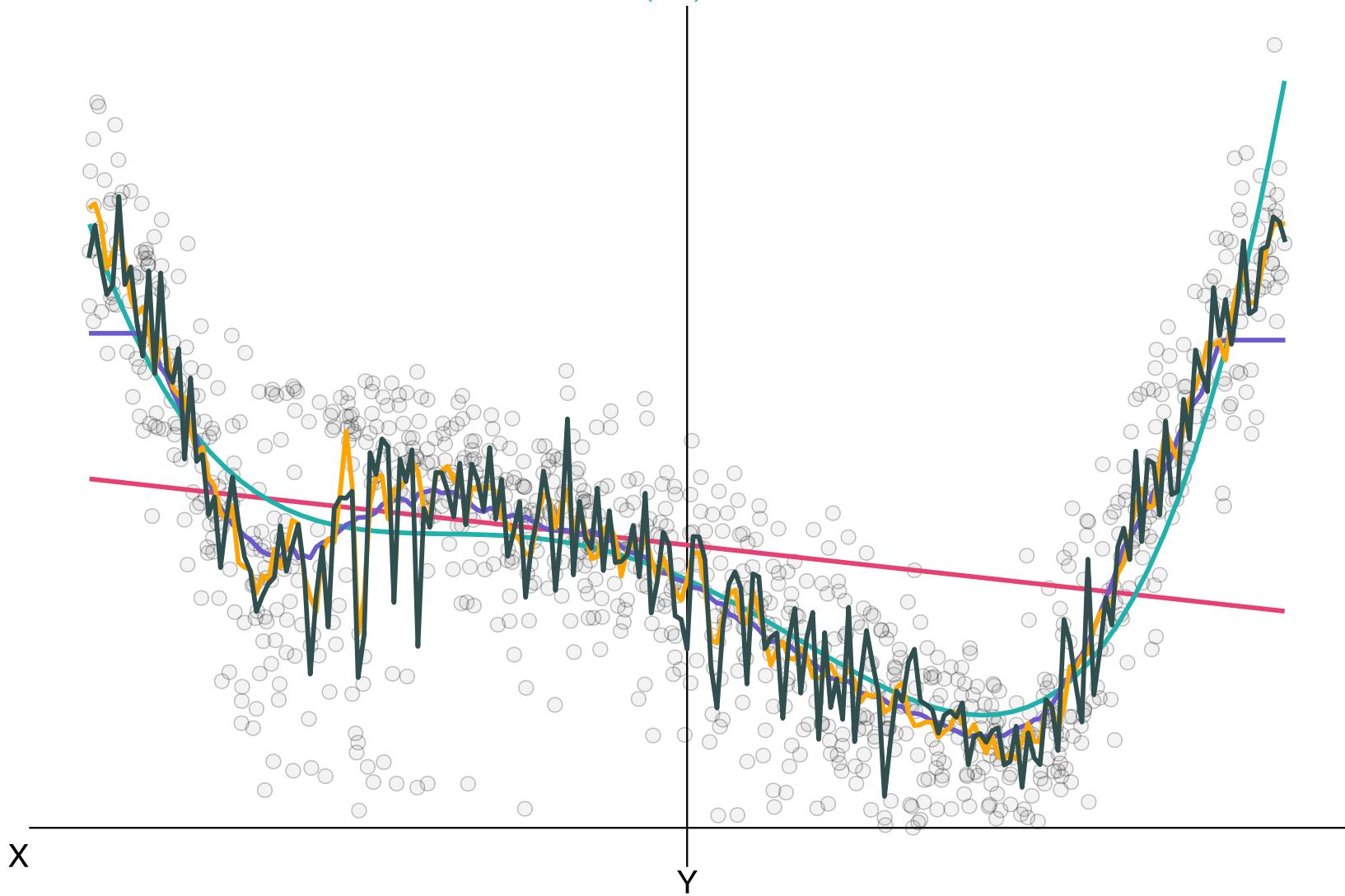
Linear regression, linear regression ( $x^4$ ), KNN (100)



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
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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
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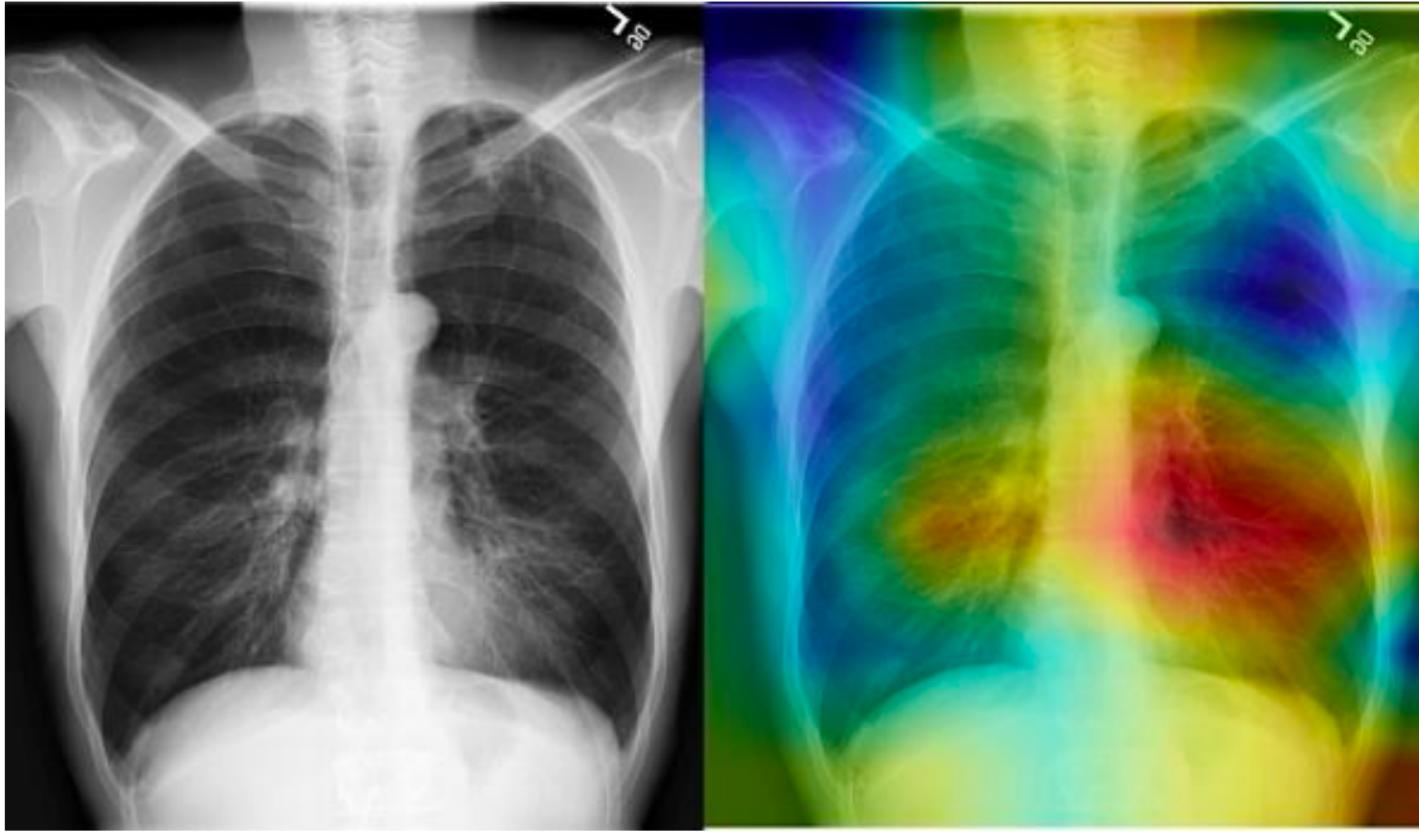
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## **Unsupervised learning**

- 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%	79.2%	100%	98.3%	20.8%
FACE++	99.3%	65.5%	99.2%	94.0%	33.8%
IBM	88.0%	65.3%	99.7%	92.9%	34.4%



**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