Lecture 000

Why are we here?

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Admin

Admin

In-class today

- **Course website:** https://github.com/edrubin/EC524W22/
- Syllabus (on website)
- In person?

TODO list

- **Today:** Sign up for Kaggle
- Upcoming readings:
  - ISL Ch1–Ch2
  - Prediction Policy Problems by Kleinberg *et al.* (2015)
- **Assignment:** This week (get to know prediction and Kaggle)

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

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

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... so?

So we want "nice"-performing estimates $\hat{y}$ instead of $\hat{\beta}$.

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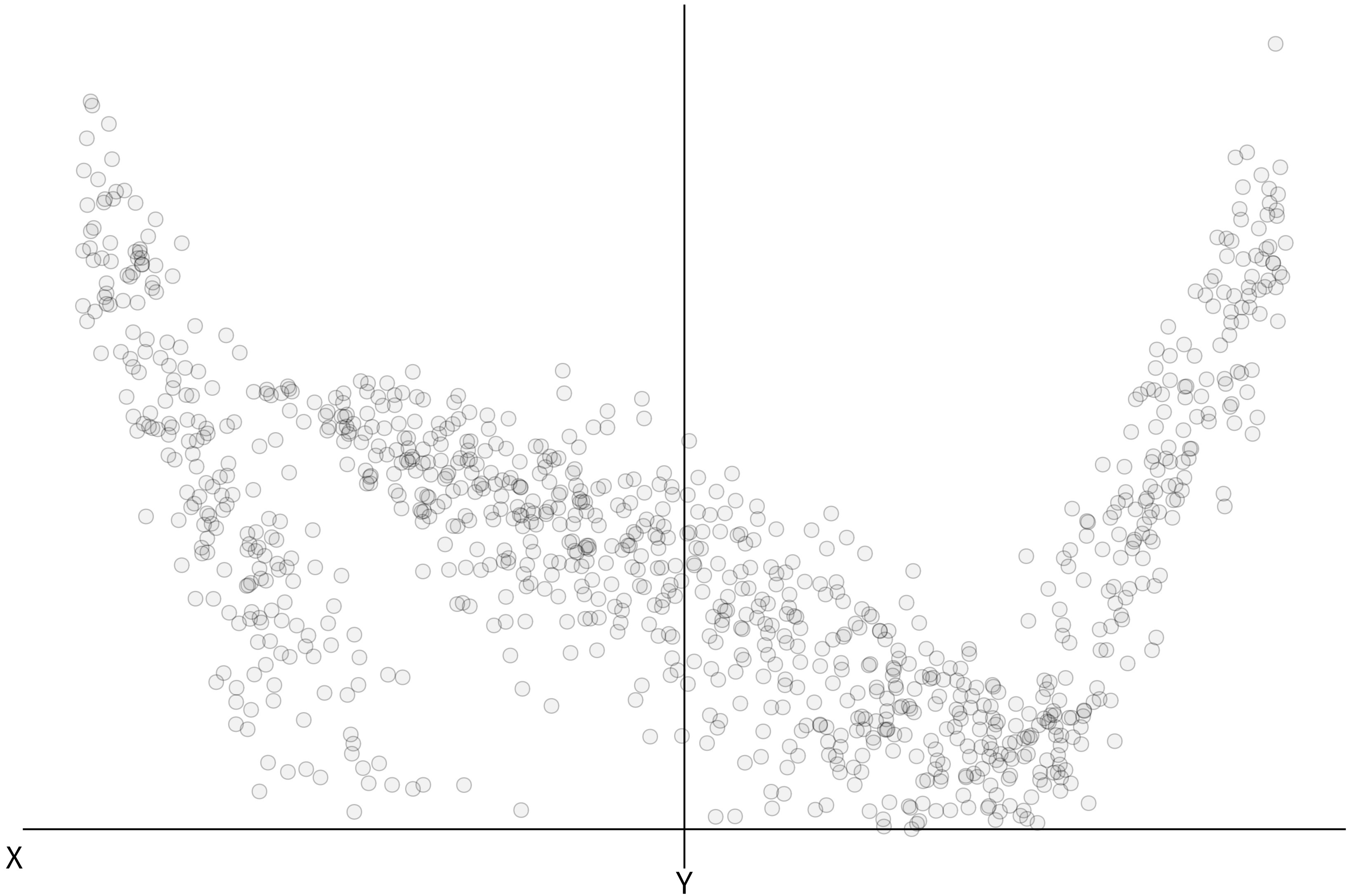
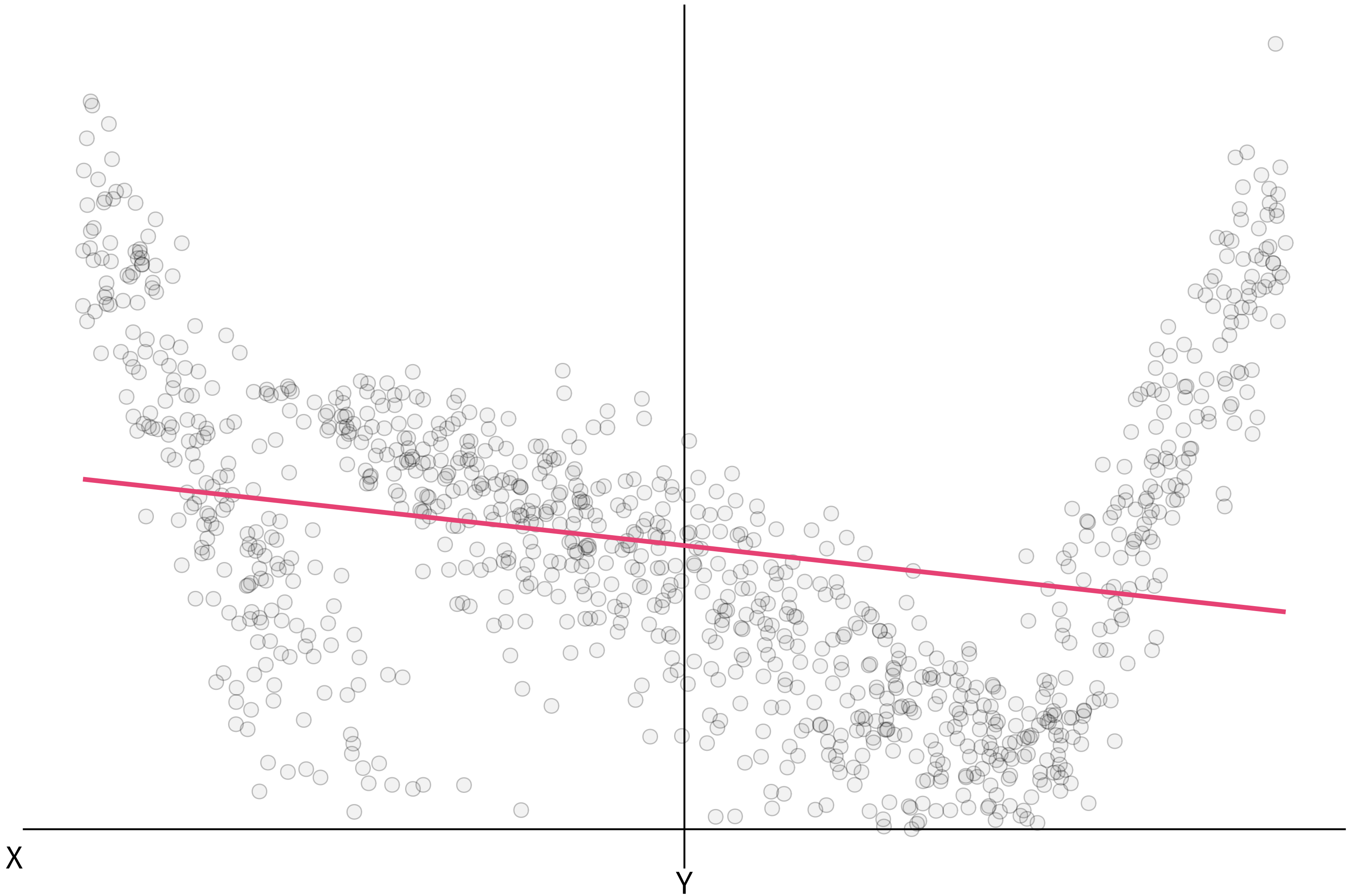
Recall Least-squares regression is a great **linear** estimator.

Data data be tricky[†]—as can understanding many relationships.

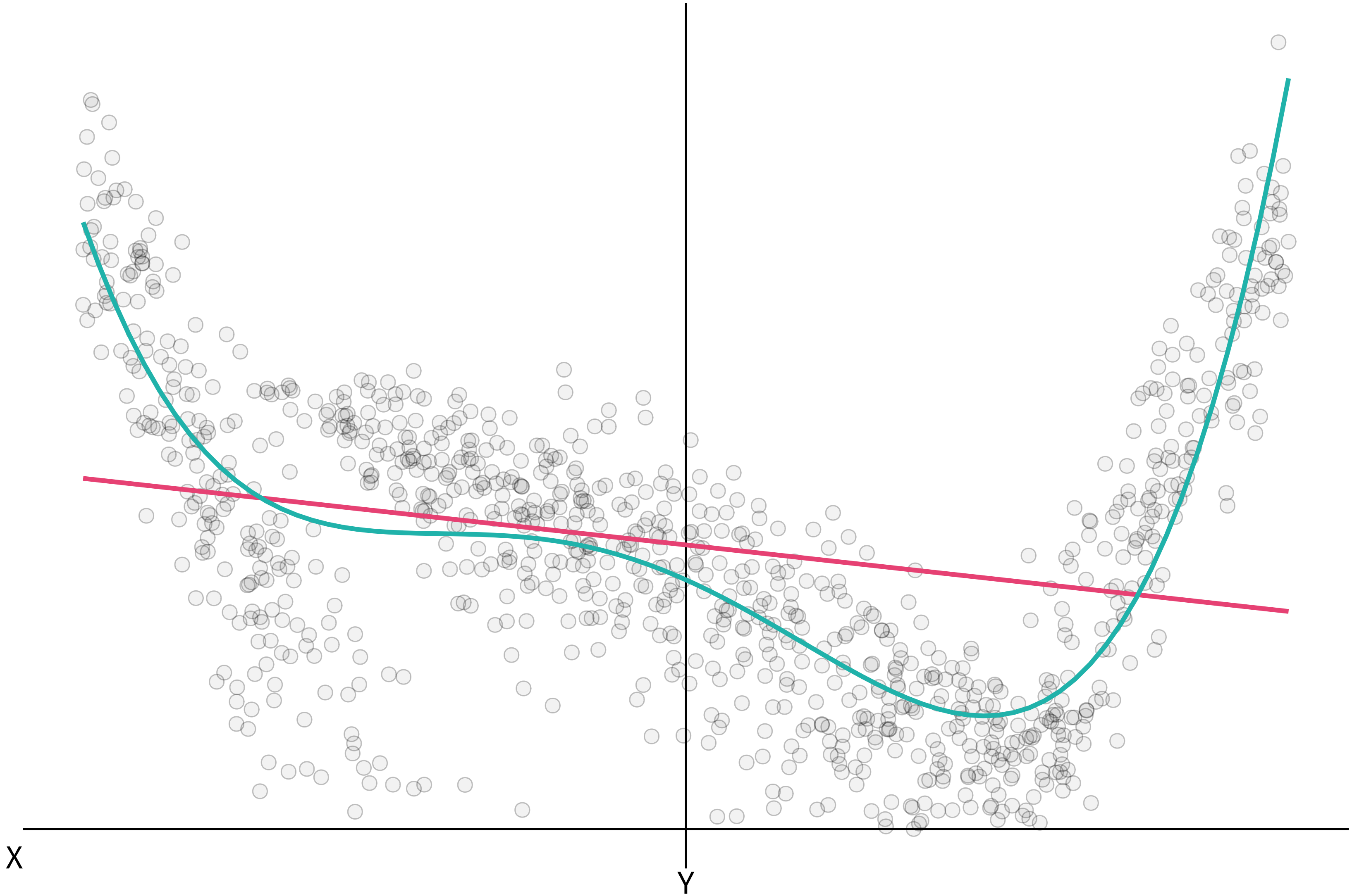
[†] "Tricky" might mean nonlinear... or many other things...

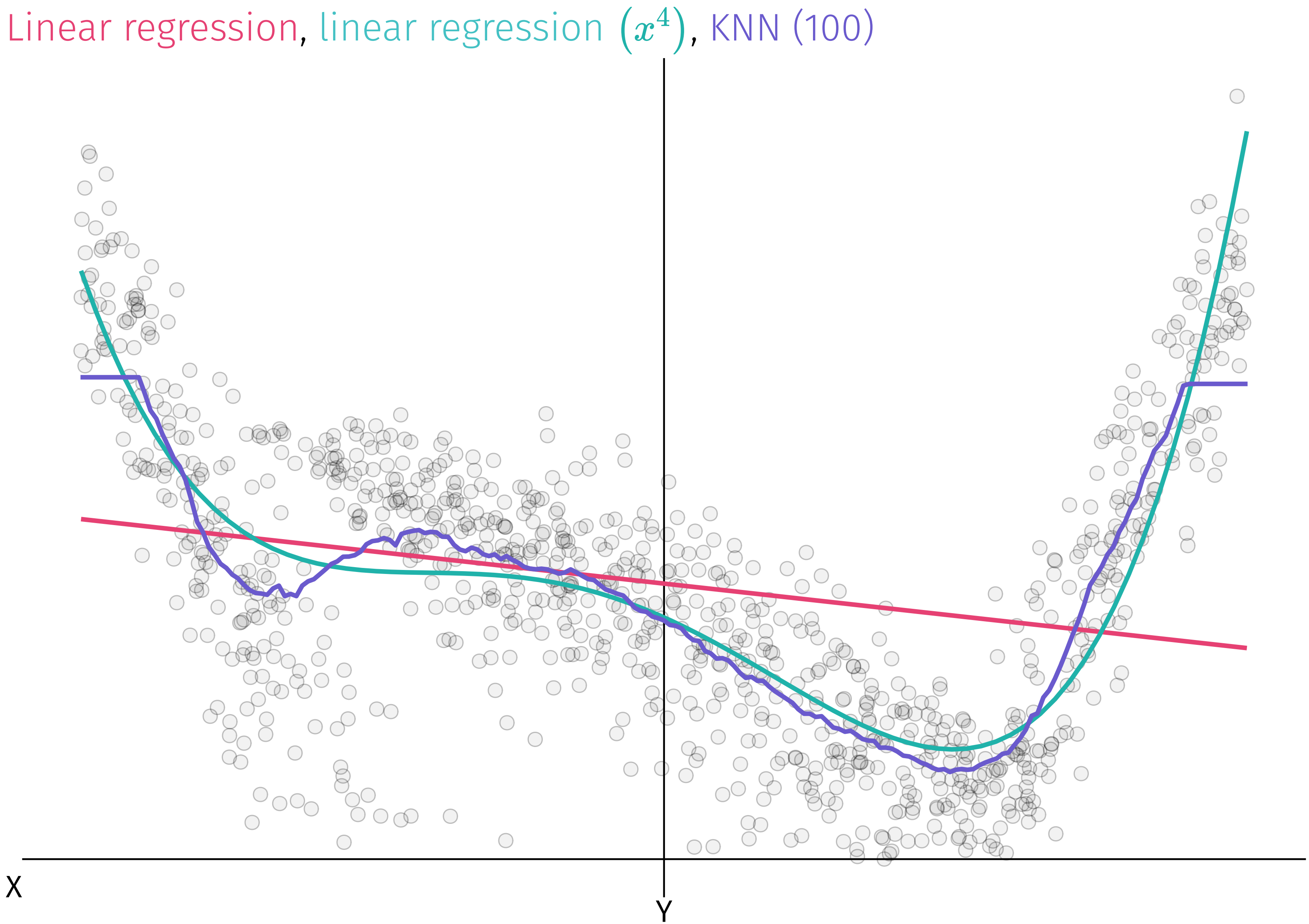

X
Y

Linear regression



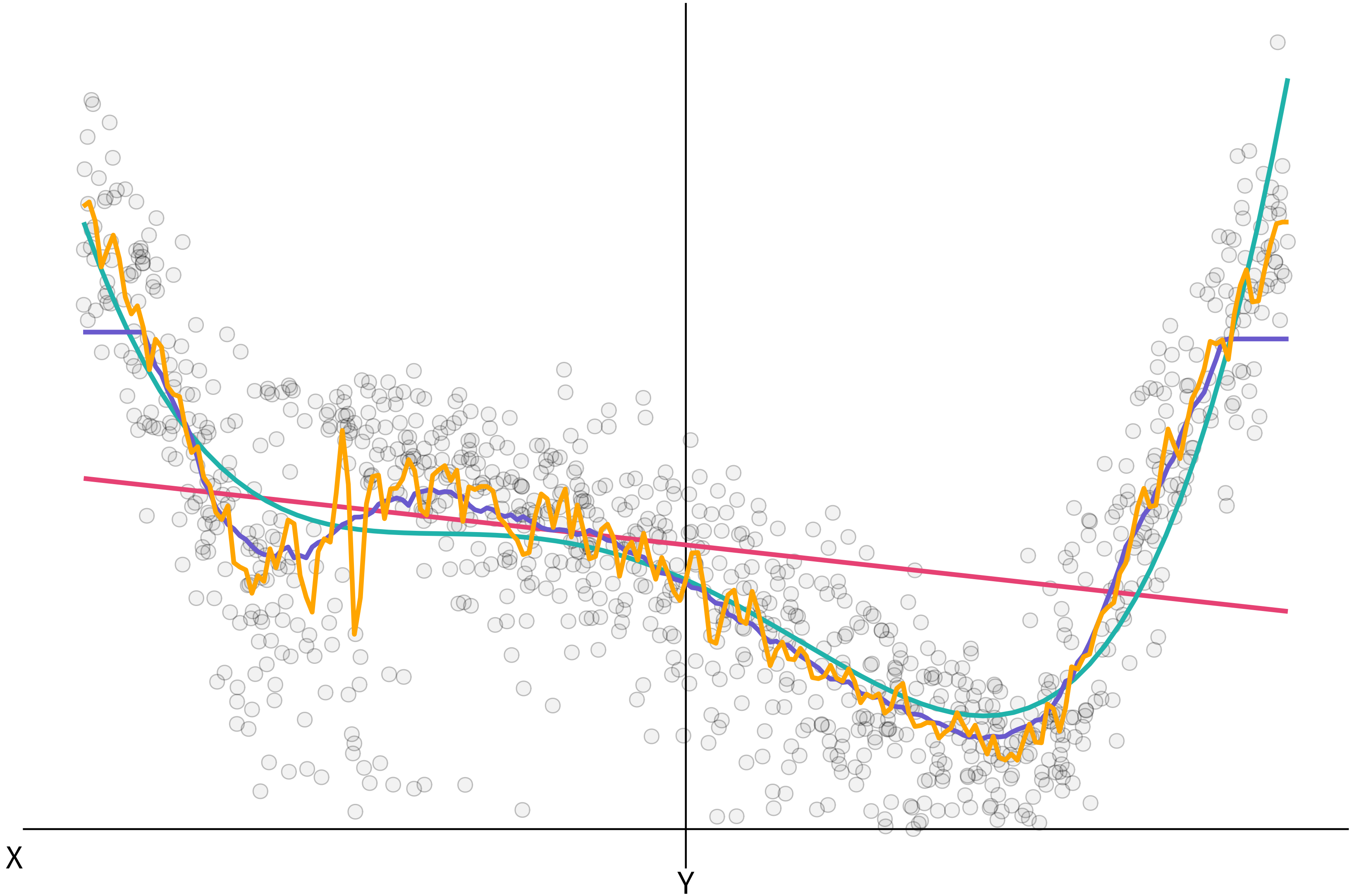
Linear regression, linear regression (x^4)

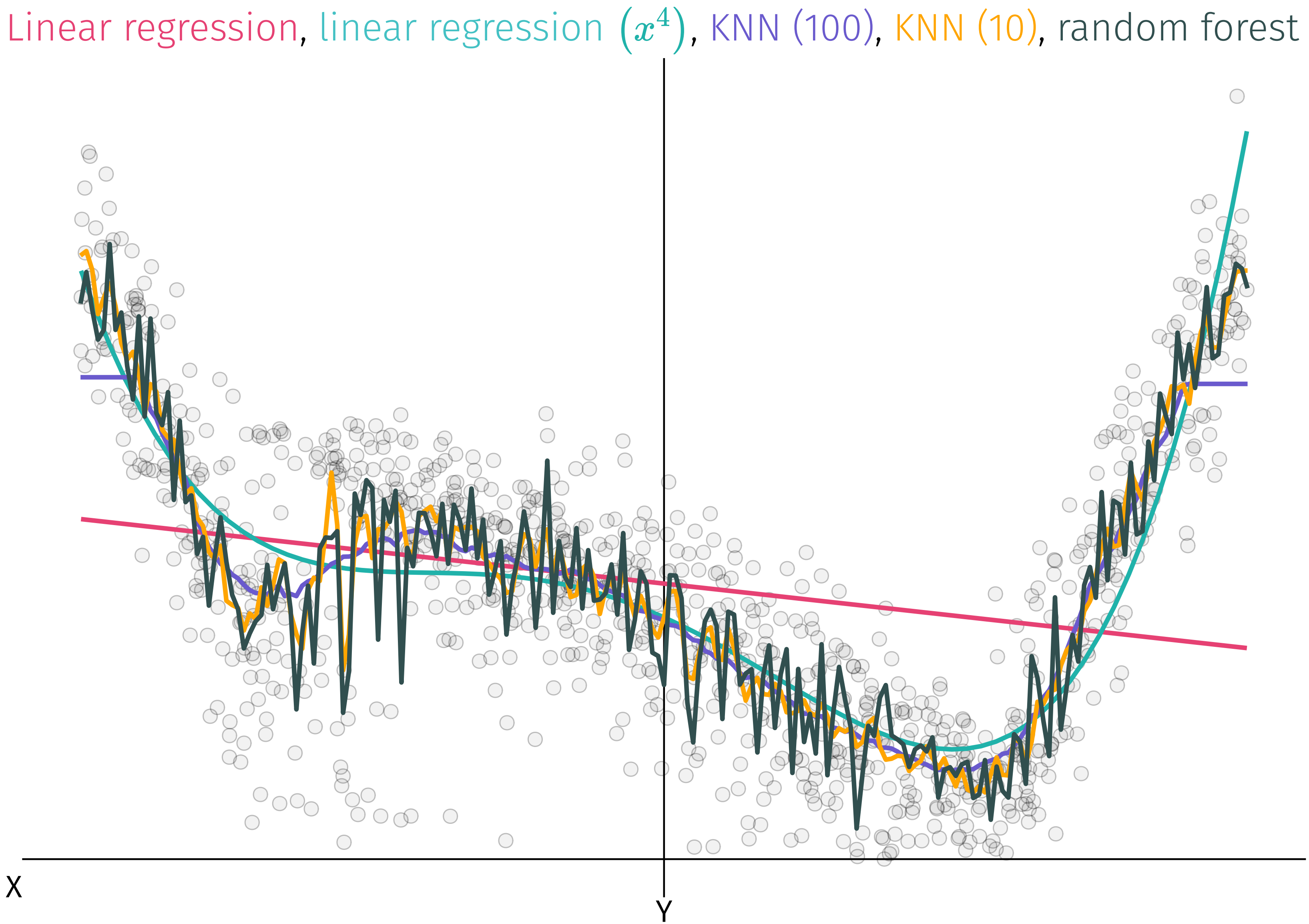




Linear regression, linear regression (x^4), KNN (100)
X
Y

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





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

Note That example only had one predictor…

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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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- Rather than {0,1}, we need to classify y_i into 1 of K classes
- *E.g.*, ER patients: {heart attack, drug overdose, stroke, nothing}

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Text analysis and **image recognition**

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

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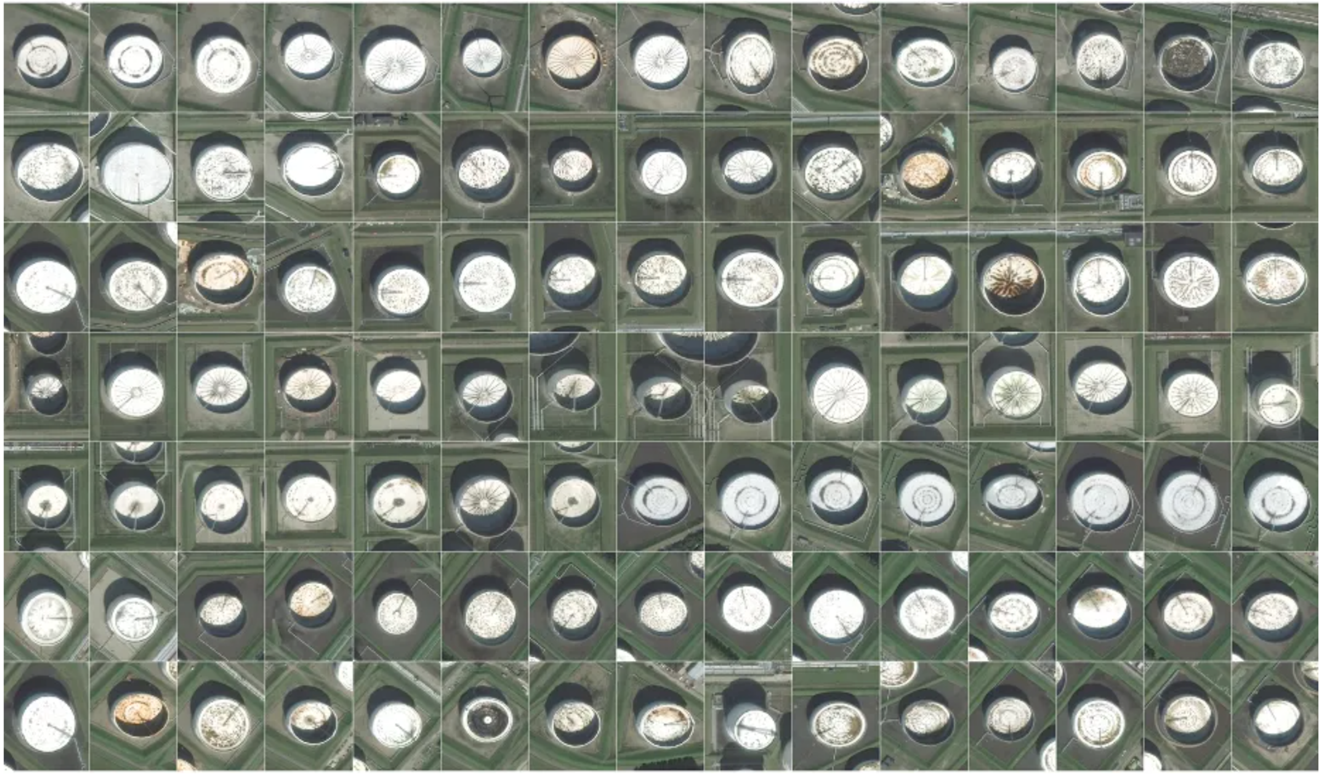
Unsupervised learning

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

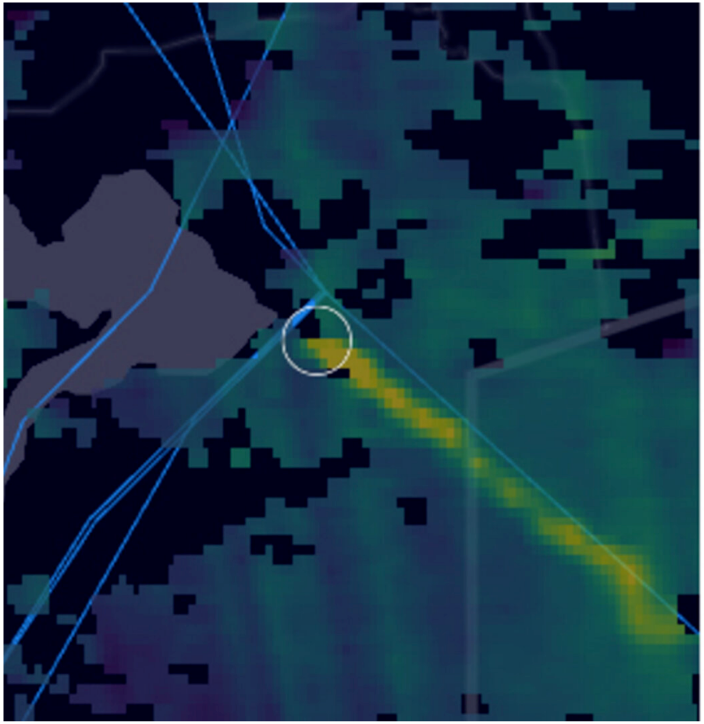
Stanford University (Stanford, CA) researchers have developed a deep-learning algorithm that can evaluate chest X-ray images for signs of disease at a level exceeding practicing radiologists.

Parking Lot Vehicle Detection Using Deep Learning

How AI Can Calculate Our Oil Surplus...From Space



ORBITAL INSIGHT/DIGITALGLOBE



Monitoring methane emissions from gas pipelines

THE NEW YORKER

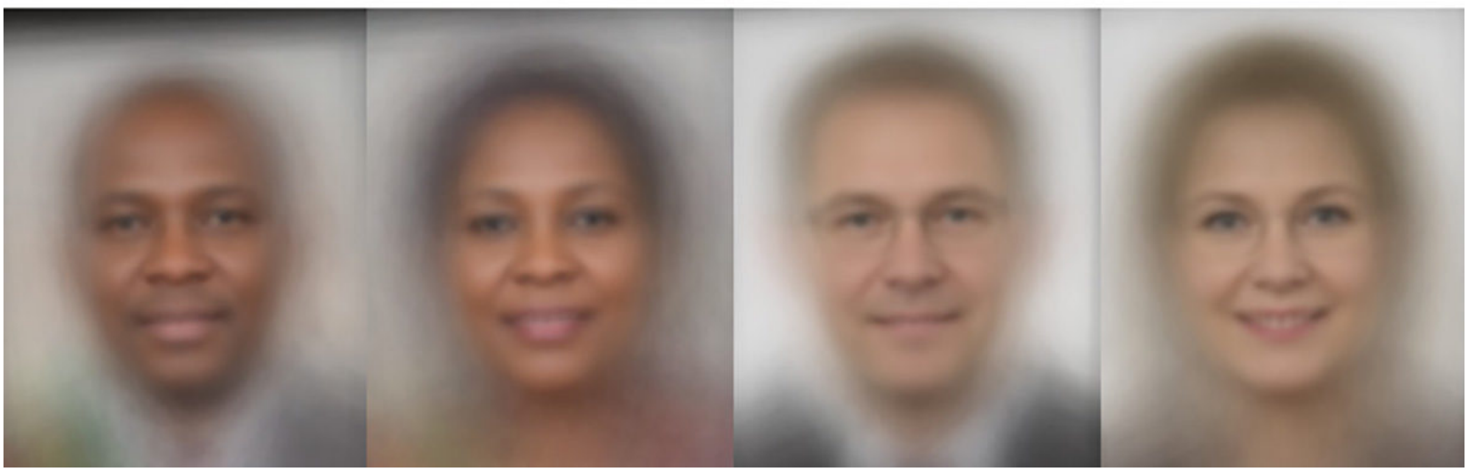
A REPORTER AT LARGE OCTOBER 14, 2019 ISSUE

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%



Takeaways?

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Mine

- Interactions and nonlinearities likely matter
- *Engineering* features/variables can be important
- *Related:* We might not even know the features that matter
- Flexibility is huge—but we still want to avoid overfitting

Next time Start formal building blocks of prediction.

Sources

Sources (articles) of images

- Deep learning and radiology
- Parking lot detection
- *New Yorker* writing
- Oil surplus
- Methane leaks
- Gender Shades

Table of contents