

# PRICING CONTEMPORARY ART

A blurred background image of a boat on water at sunset. The sky is a mix of blue and orange, with a bright sun low on the horizon. In the foreground, a dark silhouette of a boat is visible, with some colorful reflections on its hull.

Ralf Peters | Boot (Boat) | 2007

A vertical abstract artwork featuring bold, geometric shapes. It consists of several horizontal bands of different colors: dark blue at the top, followed by bright green, medium blue, light green, dark blue, light green, dark blue, and finally black at the bottom. The edges of these bands are slightly irregular, creating a dynamic, layered effect.

## MOTIVATING QUESTION

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Is it possible to systematically predict the price of an artwork based on characteristics of the work and its artist?

- Useful for sellers and buyers



## DATA

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- Scrapped from Artspace.com
- 6,400 artists
- 22,100 artworks
- 70% created since 2010, 84% since 2000
- 15,800 had price data
- Lots of other missing data, so final n = 11,227 artworks

# ARTIST-LEVEL FEATURES

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- Year of birth
- Living/dead (thanks, Nora!)
- Academic degrees
- Museum collections
- Galleries
- “Fame”



*Jamie Lau | Betting Shop (Red) | 2009*



## ARTWORK-LEVEL FEATURES

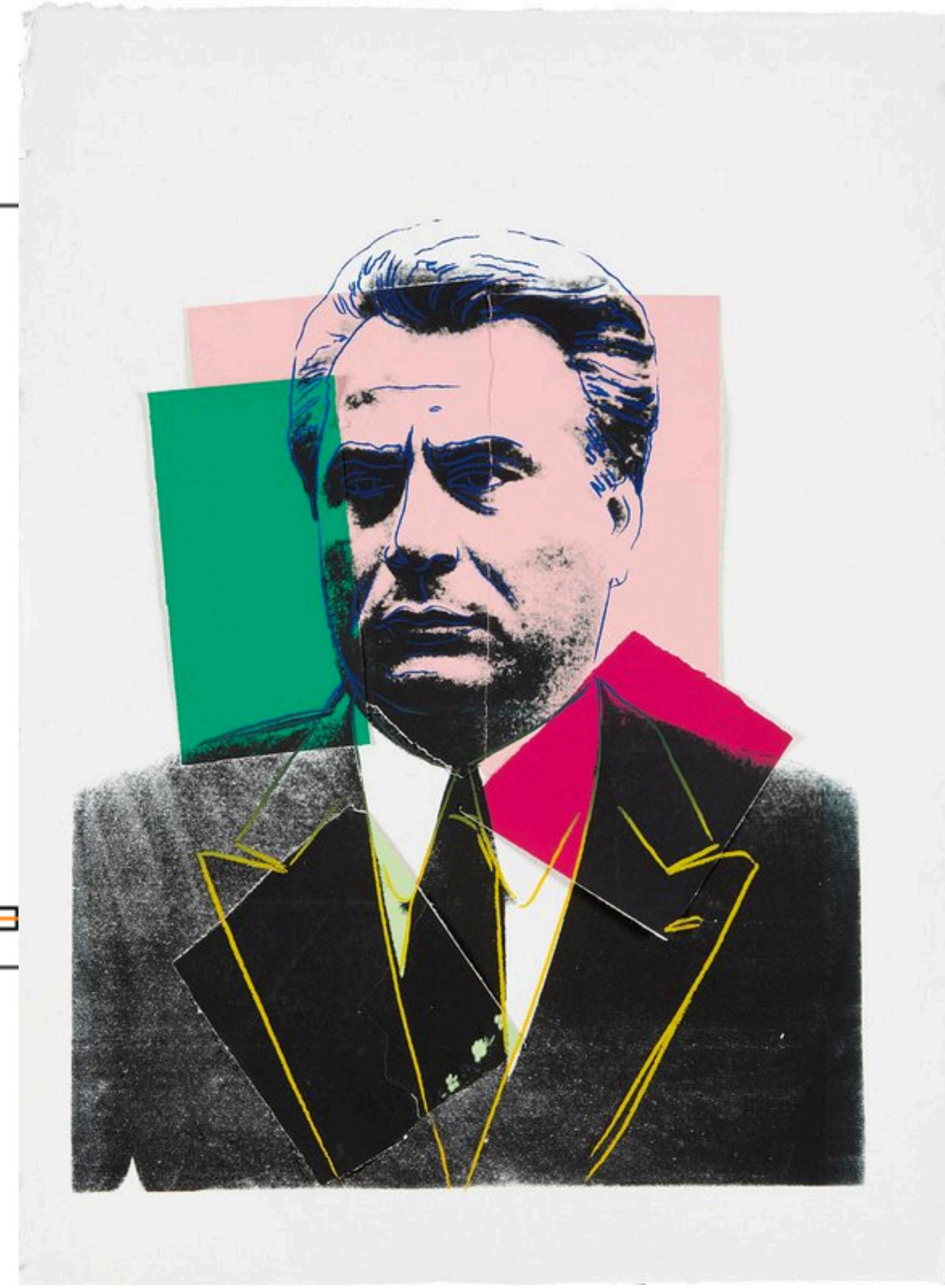
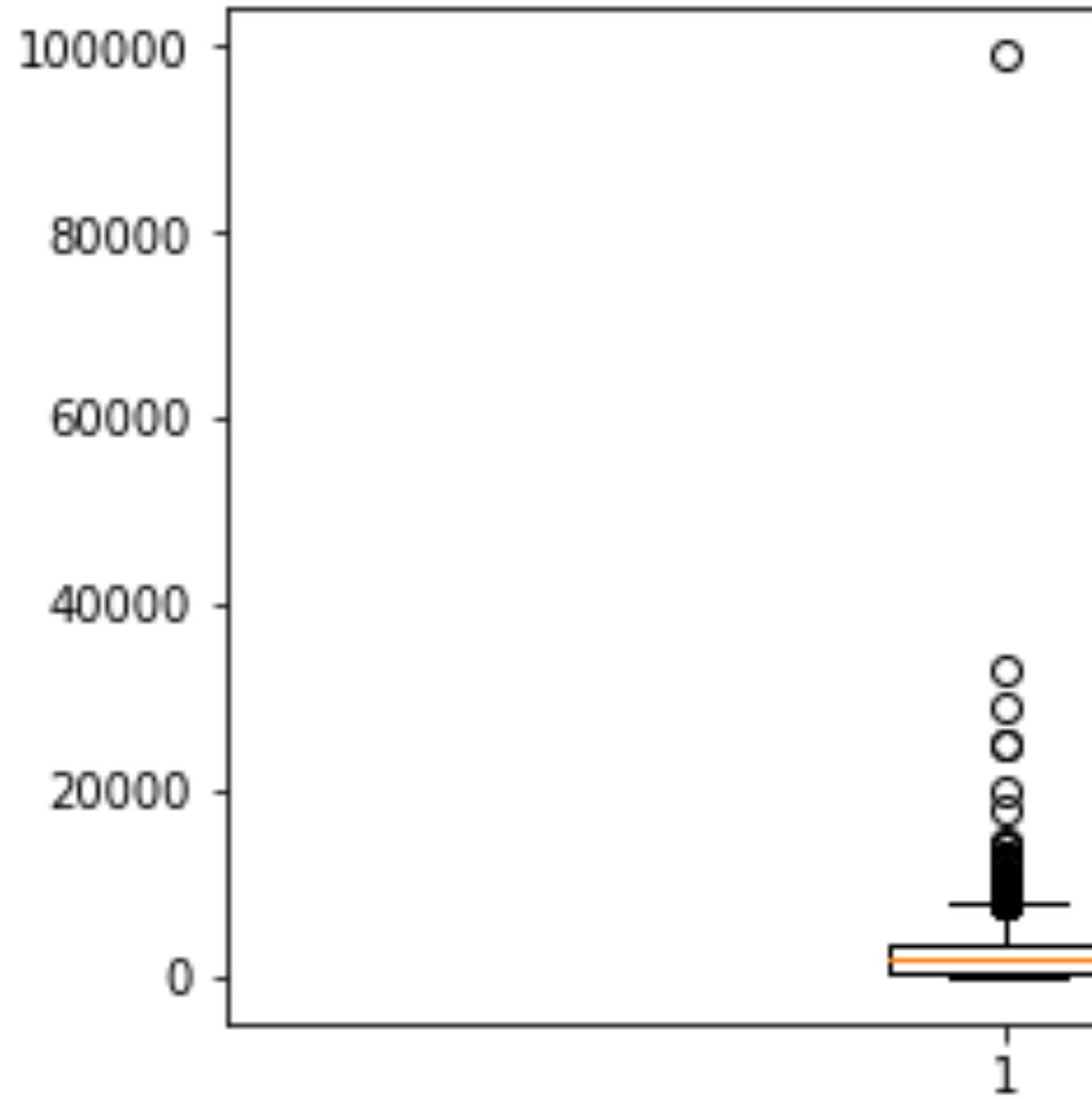
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- Decade created
- Medium (painting, print, photograph, sculpture...)
- Physical size (area)
- Edition size (e.g., unique work, or number of copies of a print)
- Signed?

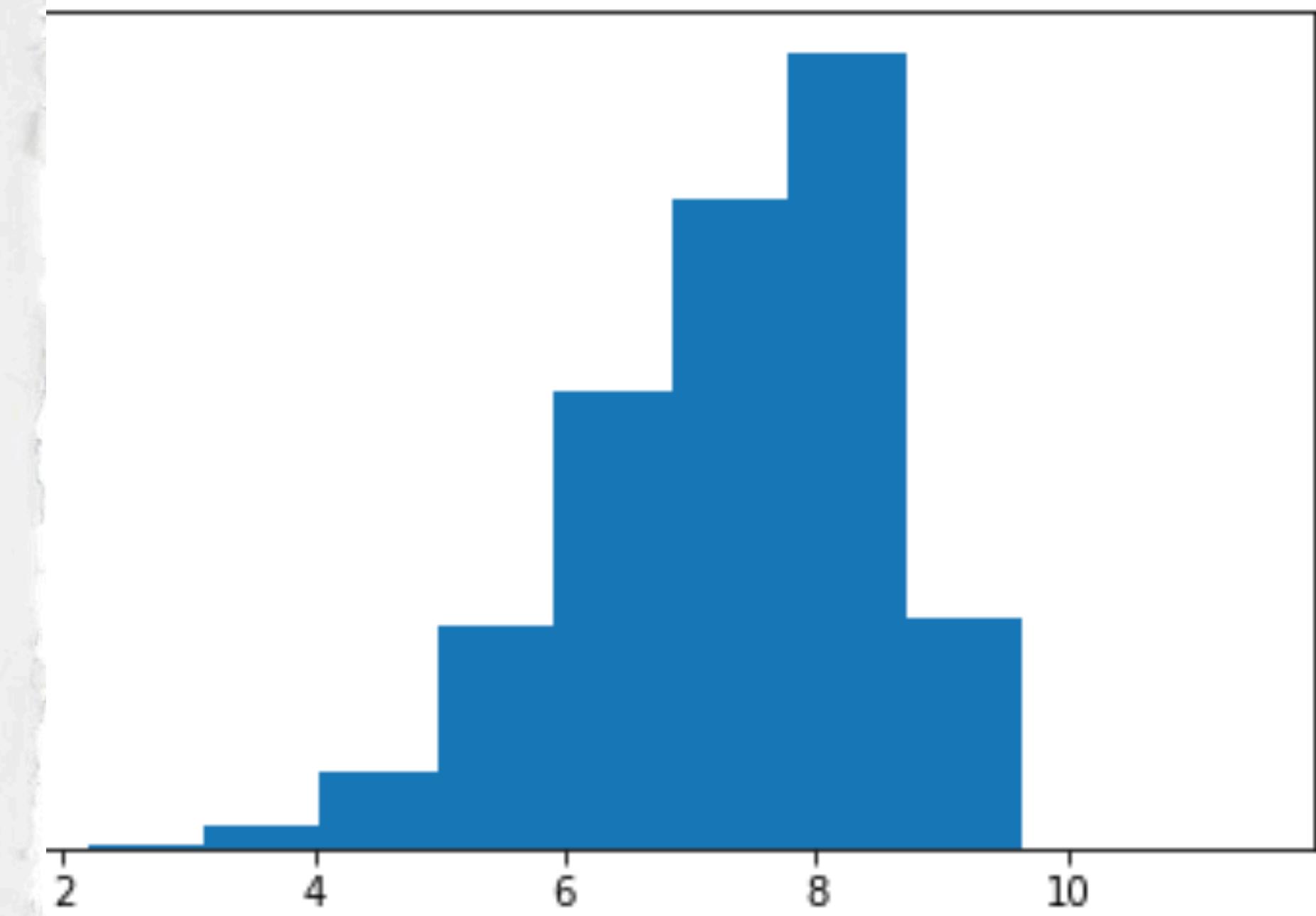
# TRANSFORMING PRICE

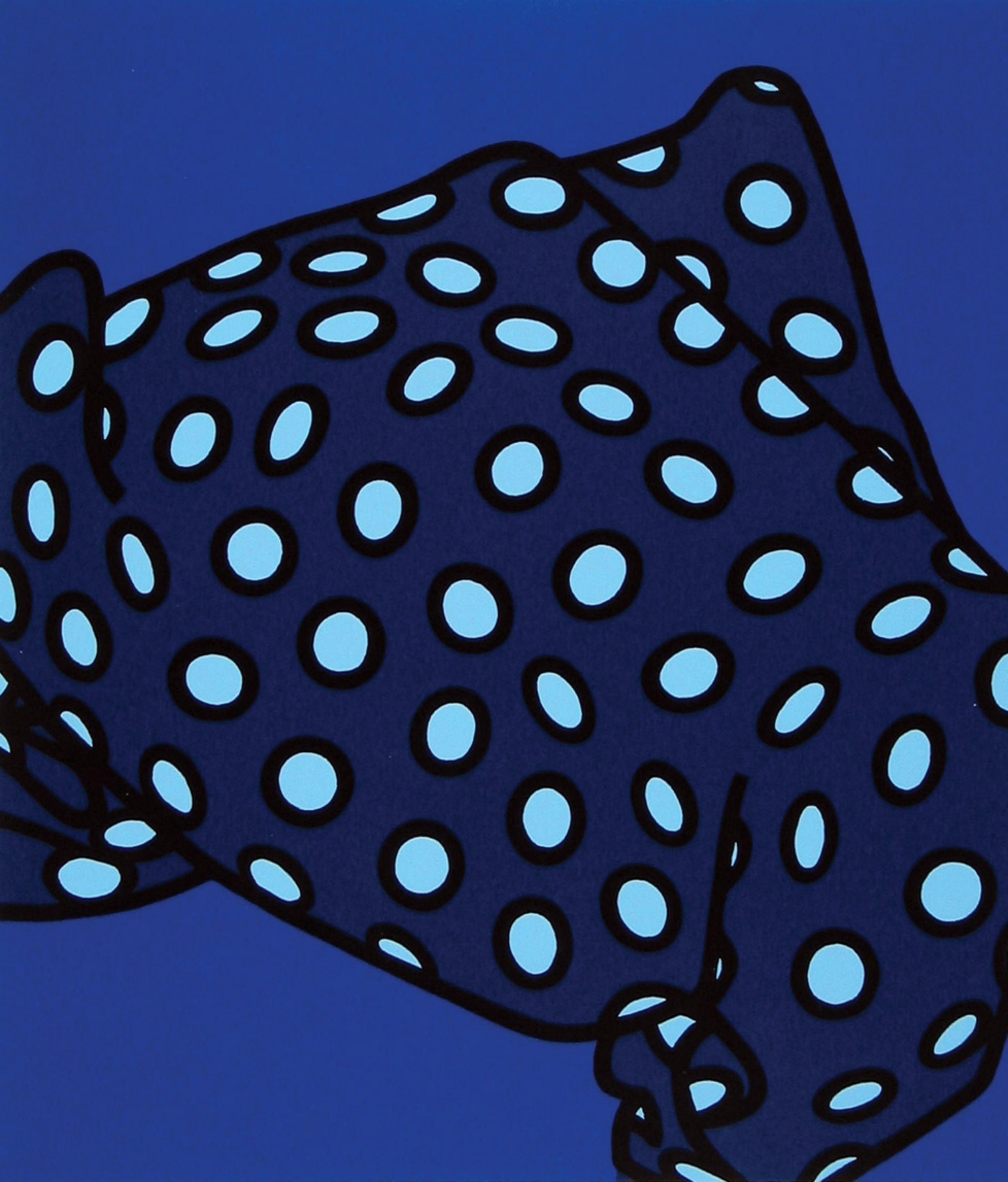
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*Price*



$\log(\text{Price})$





## ANALYSIS AND FEATURE ENGINEERING

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- Cross-validation: test/train, 80/20 split
- Linear regression
- Add polynomial features
- Add/modify features
- Regularization with LASSO and Ridge



# RESULTS

Model	Train score	Test score
Start with OLS regression	.47	.45
Add polynomial features (best degree = 2)	.63	.57
Recast “fame” as categorical	.62	.55
Add “living” feature	.63	.57
Regularize with LASSO	.62	.56
Regularize with Ridge	.63	.56



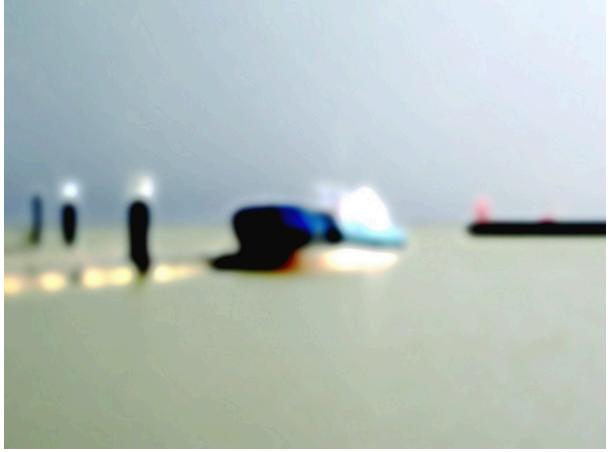
## SO, WHAT MAKES AN ARTWORK VALUABLE?

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(in descending order of scaled coeffs)

- Artwork is larger (.47)
- Not a print (.45) or “decorative arts” (.40)
- Unique work (.43) or smaller edition (.29)
- Artist is “blue-chip” (.25) or “established” (.21)

# HOW DID THE MODEL PERFORM IN THE REAL WORLD?

Artwork	Predicted	Actual	Ratio
	\$225	\$703	3.13
	\$1536	\$875	0.57
	\$1237	\$417	0.34
	\$128	\$1377	10.76
	\$1432	\$2500	1.75
	\$1448	\$524	0.36
	\$1339	\$1400	1.05
	\$833	\$500	0.60

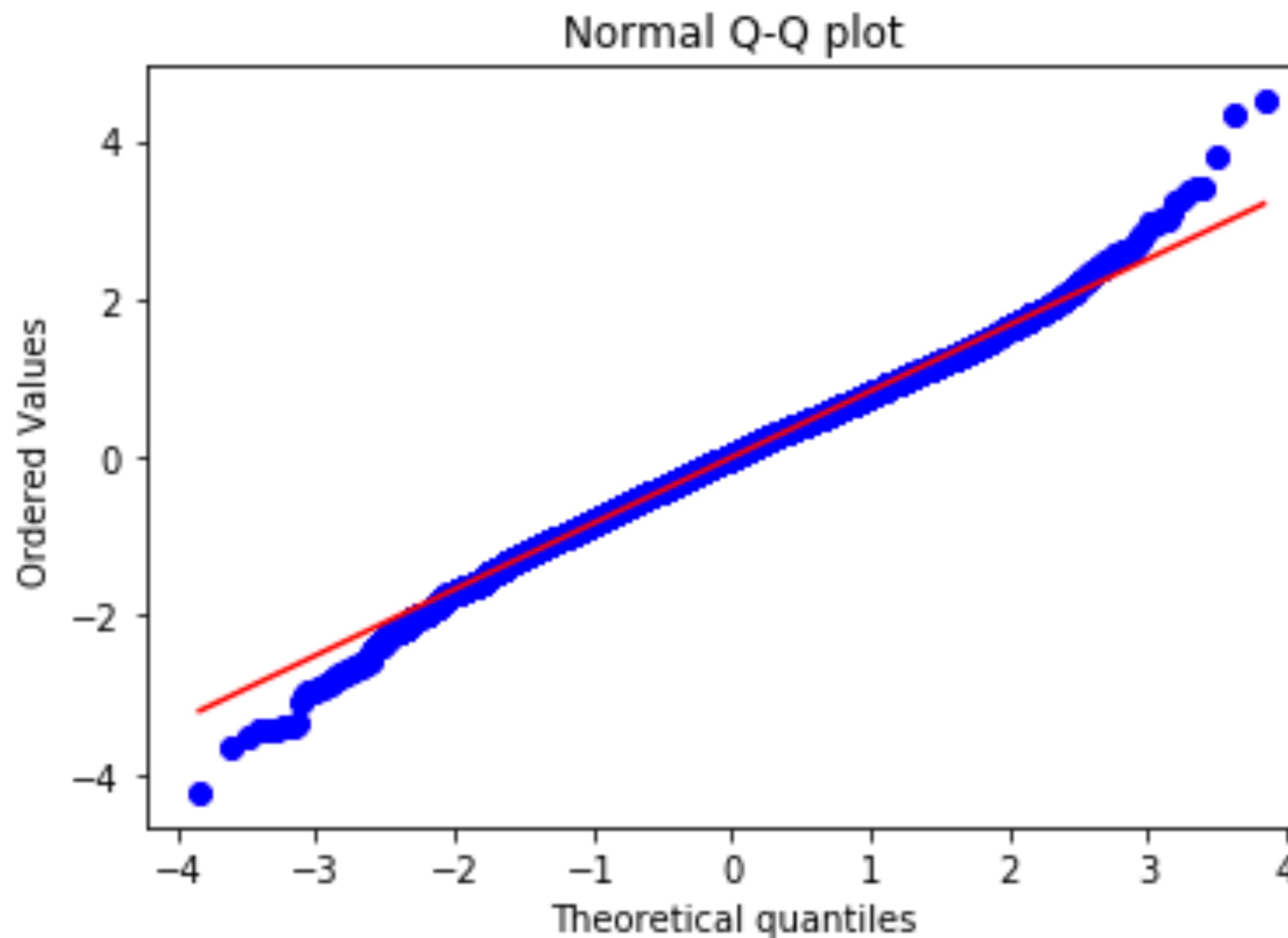
# THANK YOU



Anne Winston | *A Break in the Clouds* | 2015

# TESTING ASSUMPTION 2: RESIDUALS ARE NORMALLY DISTRIBUTED

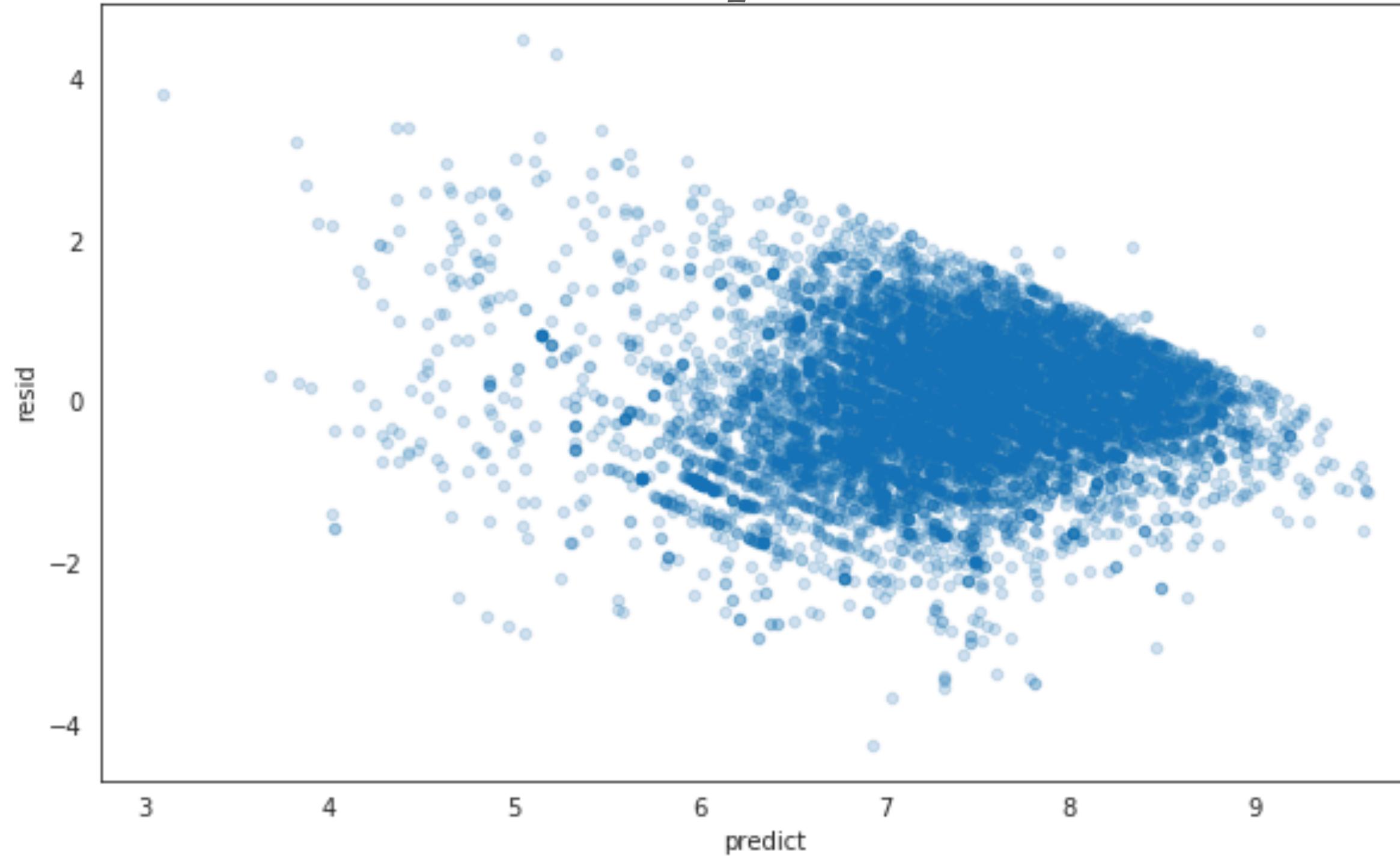
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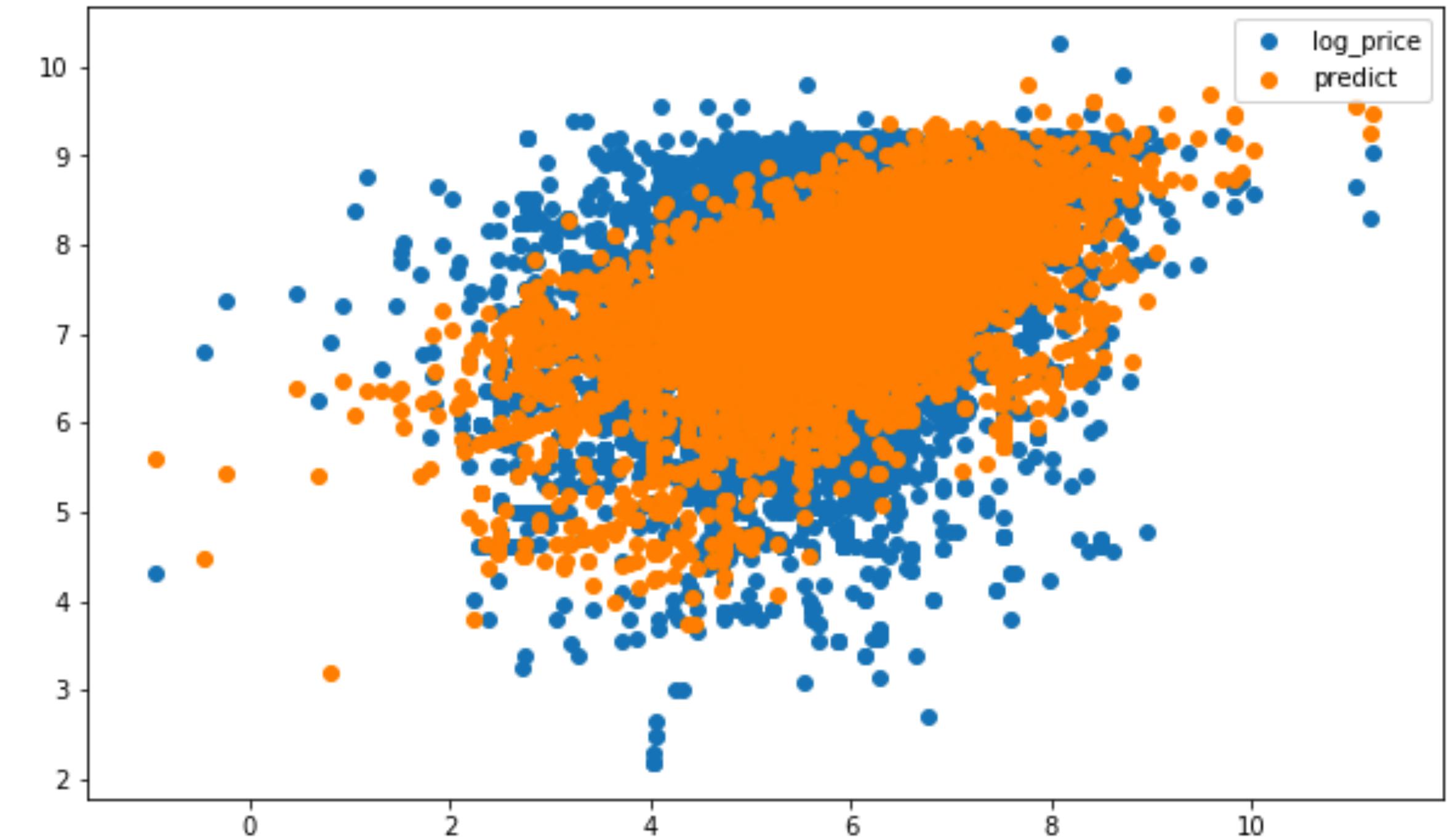
# TESTING ASSUMPTION 3: ERROR TERMS HAVE CONSTANT VARIANCE

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*Residuals vs predicted values*



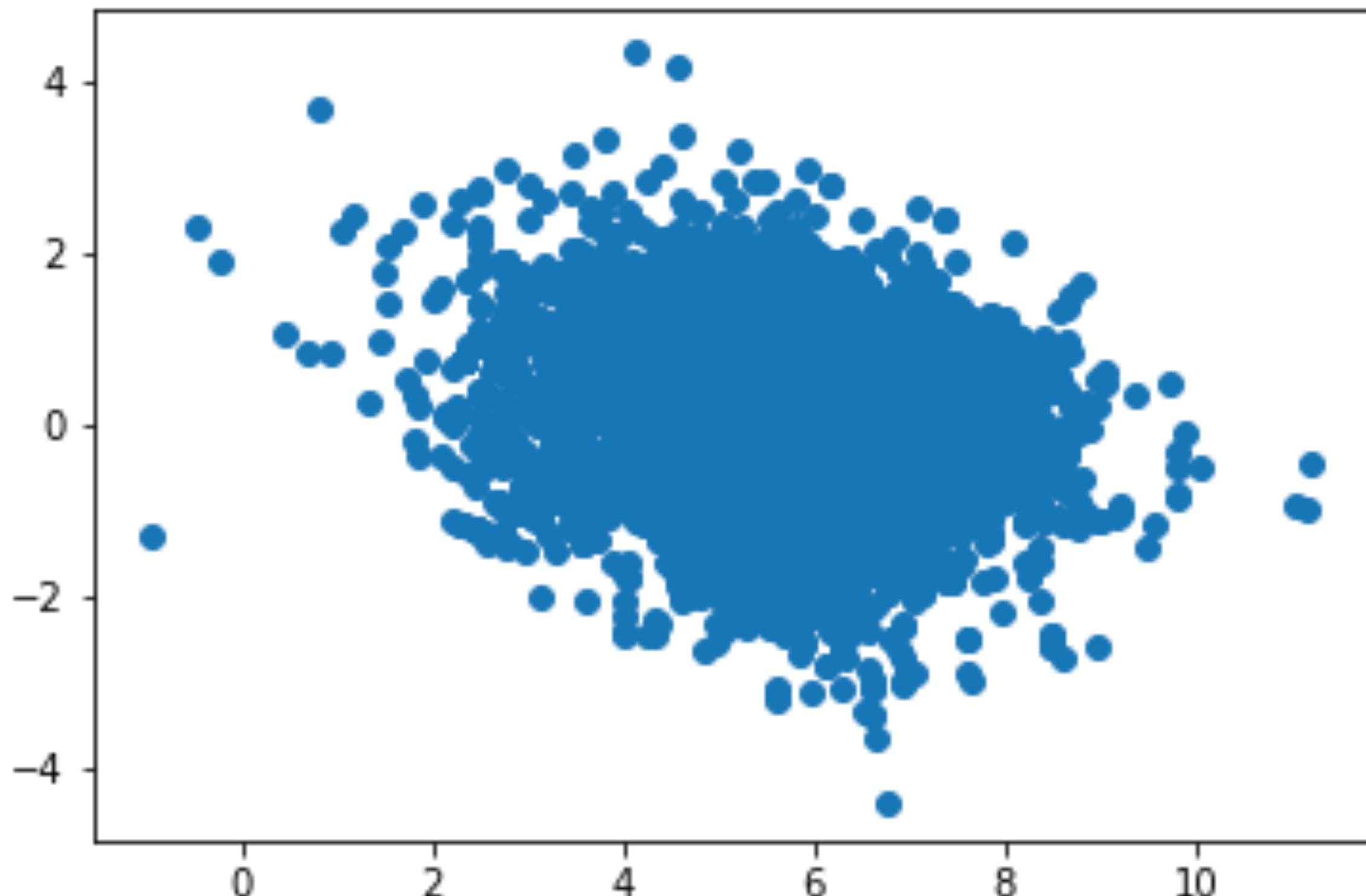
*Price vs. area*



# TESTING ASSUMPTION 4: ERRORS ARE UNCORRELATED ACROSS OBSERVATIONS

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*Residuals vs.  $\log(\text{area})$*



*Residuals by fame category*

