BUYING A WORK OF ART OR AN ARTIST?

IMPOSSIBILITY AND POSSIBILITY OF PREDICTING PRICE OF ARTWORK

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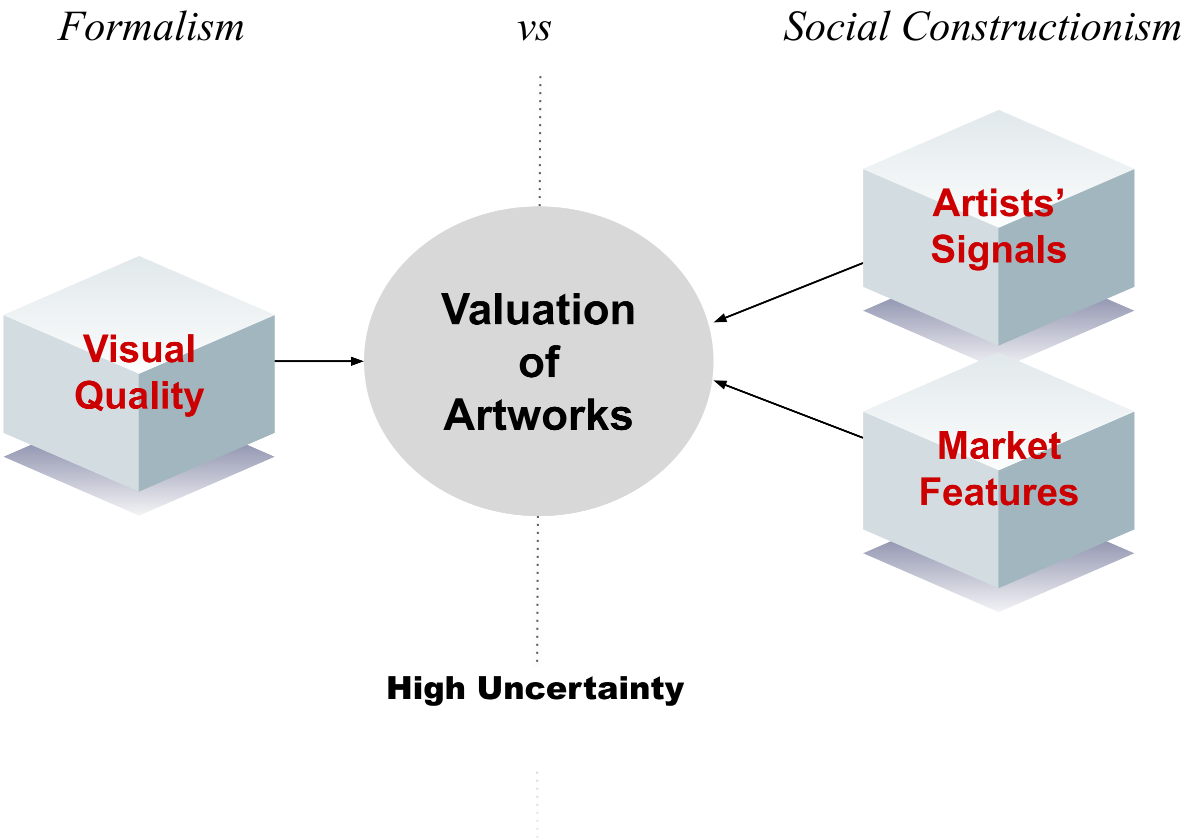
"Instead of 'It sucks' you could say, 'It doesn't speak to me.'"

Formalism vs Social Constructionism

Valuation / Pricing of Artworks



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CHINA ART MARKET REPORT – JULY 2015

REPORT DETAILS:

Date:	10 July 2015
Number of Pages:	8
Name of Researchers:	Anders Petterson, Yu Chen
Type of Report:	Market Report

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Overall Chinese art sales up first half of 2015, but Chinese contemporary sales drop 44%.

Slowing economic growth in China's and an es… campaign introduced by the government last ye… art market growth in the second half of 2014. H… 2015, recovered the losses from the previous s… sales for the top four auction houses (Sotheby'… China Guardian) raised a total of $1.6 billion, u… 2014. The total came in 2.5% lower than Spring… 39% lower than the market peak in Spring 2011… Although the overall Chinese art market did we…

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1. Darja Bajagić	1. Josh Kline	1. Sadie Benning	1. Njideka Akunyili Crosby	1. Nate Lowman	1. Carroll Dunham
2. Danny Fox	2. Jonathan Gardner	2. Mernet Larsen	2. Jordan Wolfson	2. Alex Israel	2. Kerry James Marshall
3. Louise Bonnet	3. Max Hooper Schneider	3. Latifa Echakhch	3. Nicole Eisenman	3. Tauba Auerbach	3. Philip Guston
4. Nathan Zeidman	4. Melike Kara	4. Aaron Garber-Maikovska	4. Mary Weatherford	4. Torey Thornton	4. Eric Fischl
5. Paul Kremer	5. Orion Martin	5. Jana Euler	5. Jonas Wood	5. Seth Price	5. George Condo
6. Aaron Fowler	6. Brian Calvin	6. Jennifer Guidi	6. Henry Taylor	6. Math Bass	6. Kenny Scharf
	7. Mira Dancy	7. Nina Chanel Abney	7. Olafur Eliasson	7. Danh Võ	7. Sol LeWitt
			8. Ugo Rondinone	8. Jamian Juliano-Villani	8. Mike Kelley
			9. Joe Bradley	9. Oscar Murillo	9. Nam June Paik
			10. Avery K. Singer		

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Who Are the Top 100 Most Collectible Living Artists?

artnet News, Thursday, May 26, 2016

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MARKET

Who Are the Most Undervalued Artists in Today's Market?

Henri Neuendorf, Thursday, November 12, 2015

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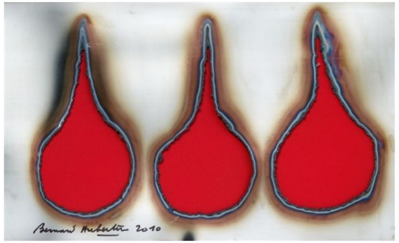
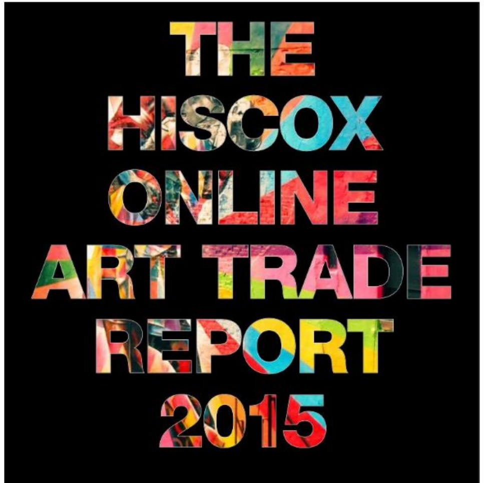


Most Popular



Data

36,549 records of artwork of 590 living contemporary artists, spanning 23 countries for 17 years (1996 to 2012)

Visual Information (8971 features)

- Publicly available thumbnail images

Market Information (8 features)

- Year
- Auction House tier
- Market growth
    - Continent level
    - Country level

Artist information (30 features)

- Age / Gender / Nationality/ Education / Award / Biennale / Artistic Ranking / Solo and Group exhibitions / Private and Public Collections / Location of living and working
- Matched Genre and Country
- Previous Year Price level (Max Mean Median)
- Previous sales (5 / 10 transactions; Max Mean Median)

Buying an Artwork: Computer Vision Analysis of Visual Content

What is form? How can we describe it numerically?

- The digital image is already an imperfect representation of a real object

Buying an Artwork:
Computer Vision Analysis of Visual Content

What is form? How can we describe it numerically?

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- …and a low resolution thumbnail doesn't help.

Buying an Artwork:
Computer Vision Analysis of Visual Content

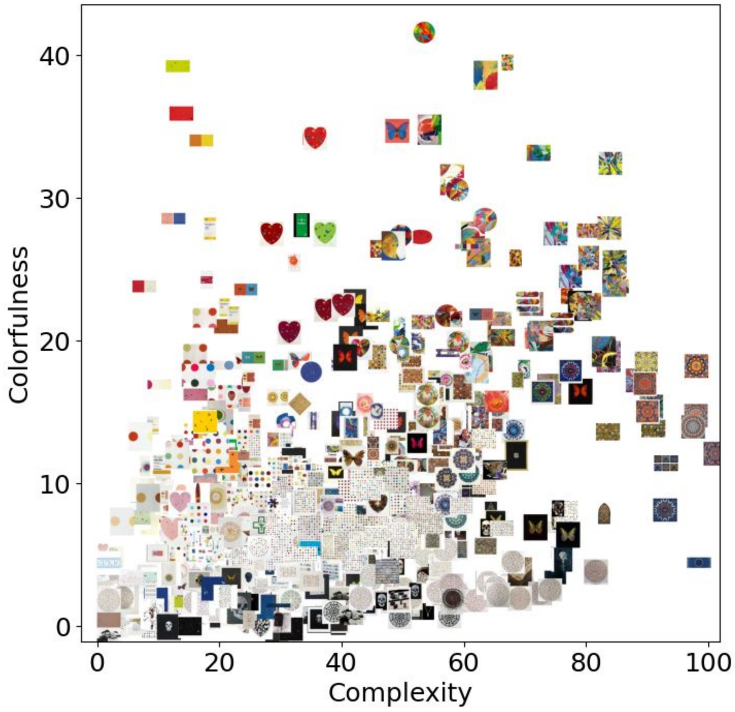
What is form? How can we describe it numerically?

- The digital image is already an imperfect representation of a real object
- …and a low resolution thumbnail doesn’t help.

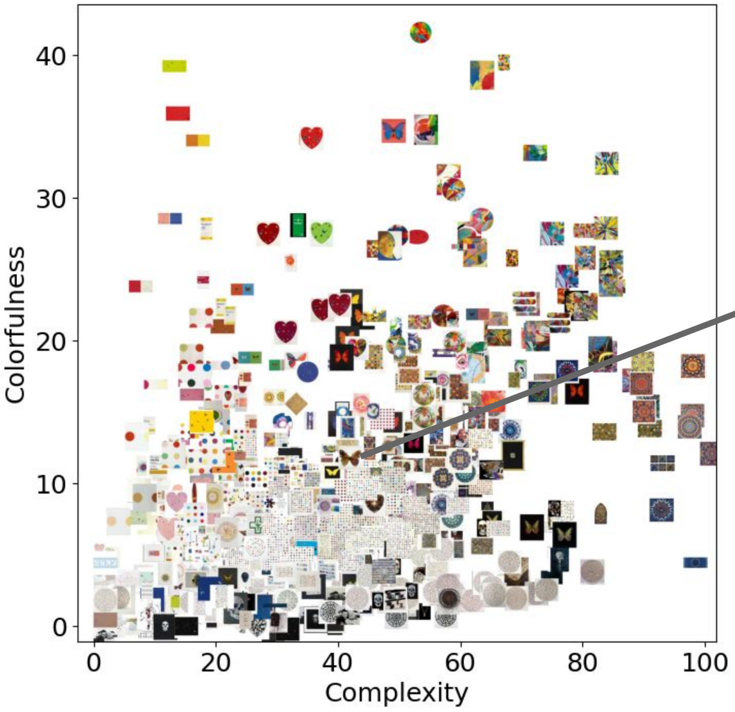
Some ideas:

- color (pixels have color)
- shape (how edges fit together)
- composition (spatial distribution of edges)
- recognizable objects (image classification)

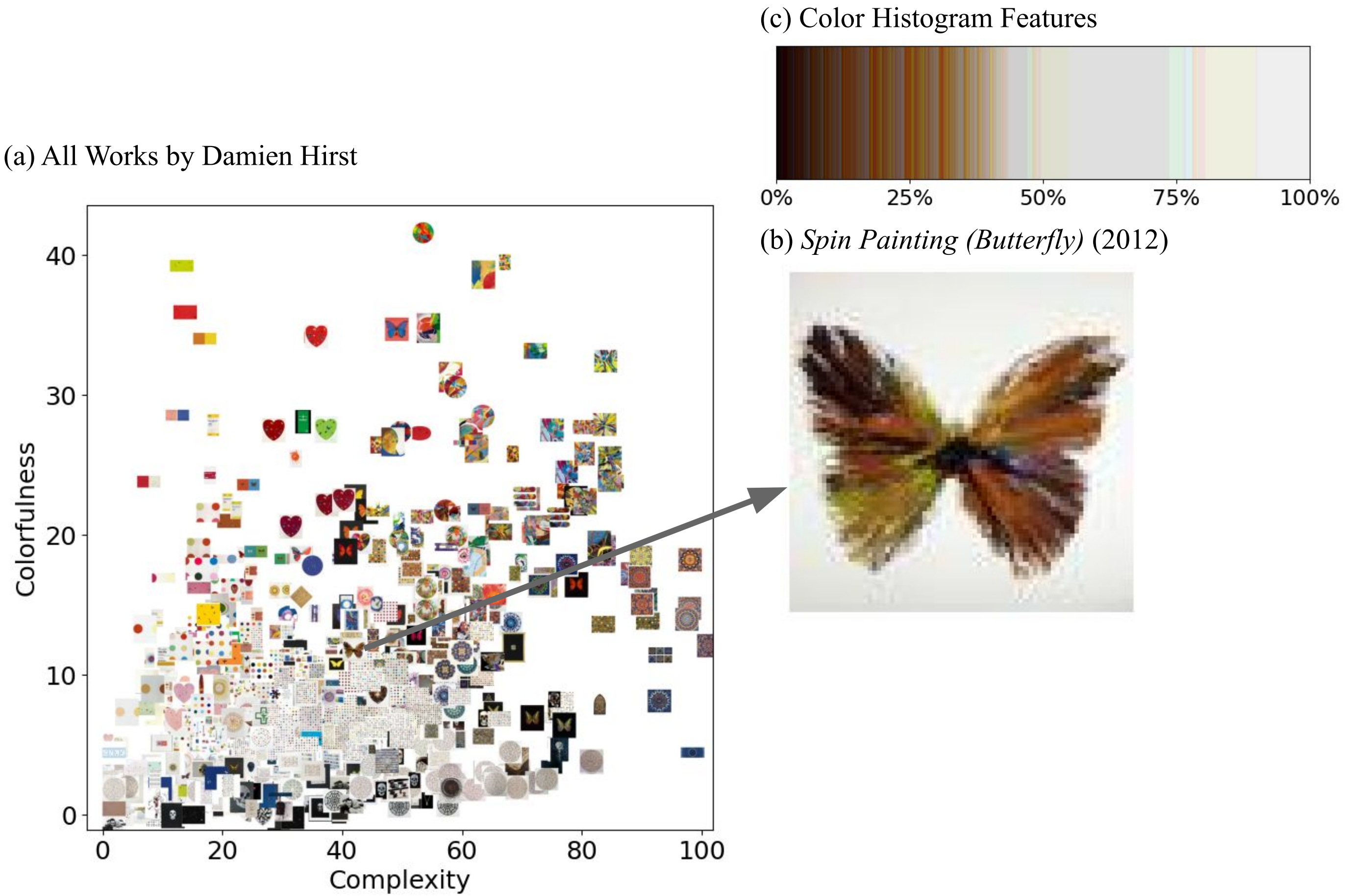
(a) All Works by Damien Hirst

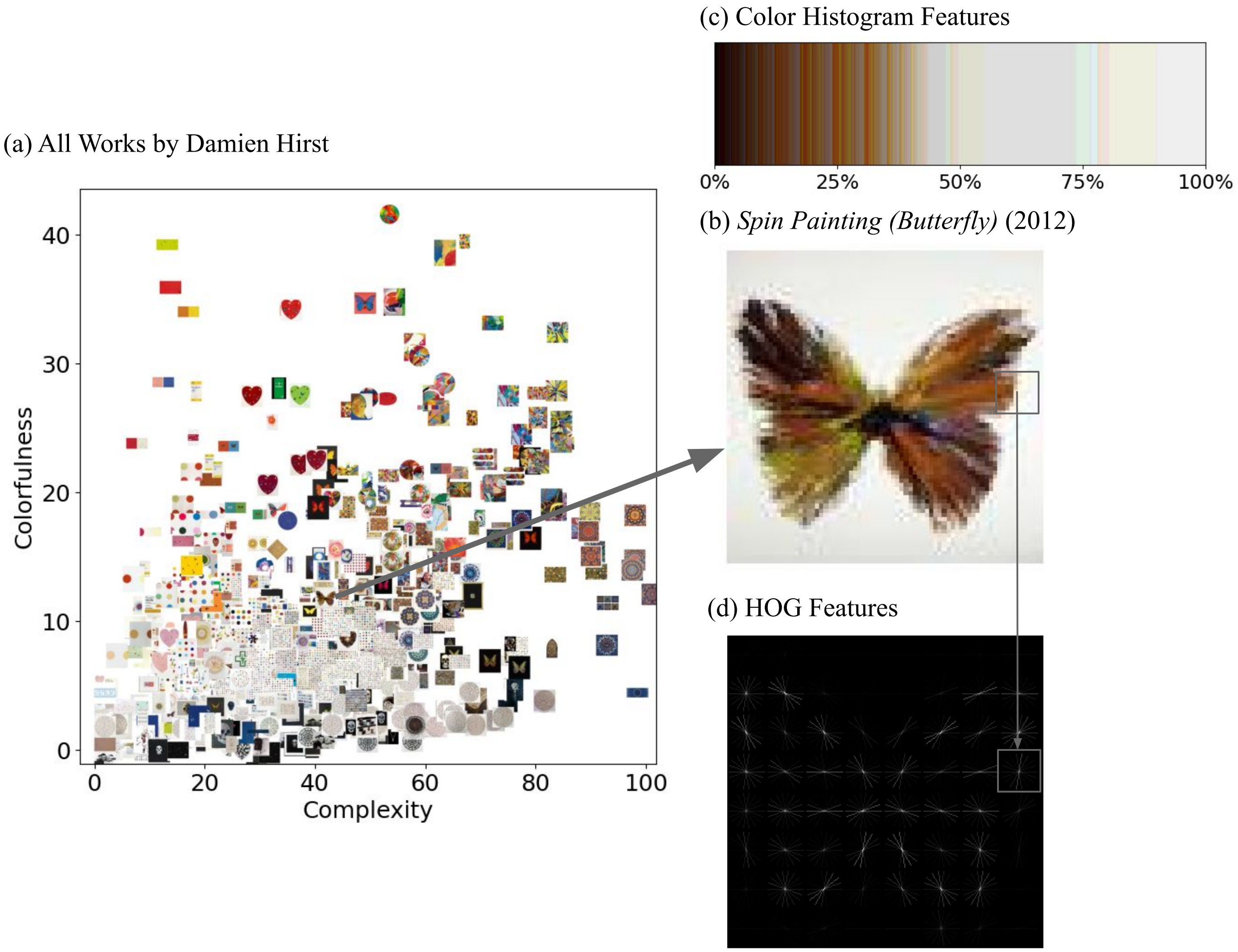


(a) All Works by Damien Hirst



(b) *Spin Painting (Butterfly)* (2012)


(c) Color Histogram Features
0%
25%
50%
75%
100%
(b) *Spin Painting (Butterfly)* (2012)
(a) All Works by Damien Hirst
Colorfulness
0
10
20
30
40
0
20
40
60
80
100
Complexity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75%
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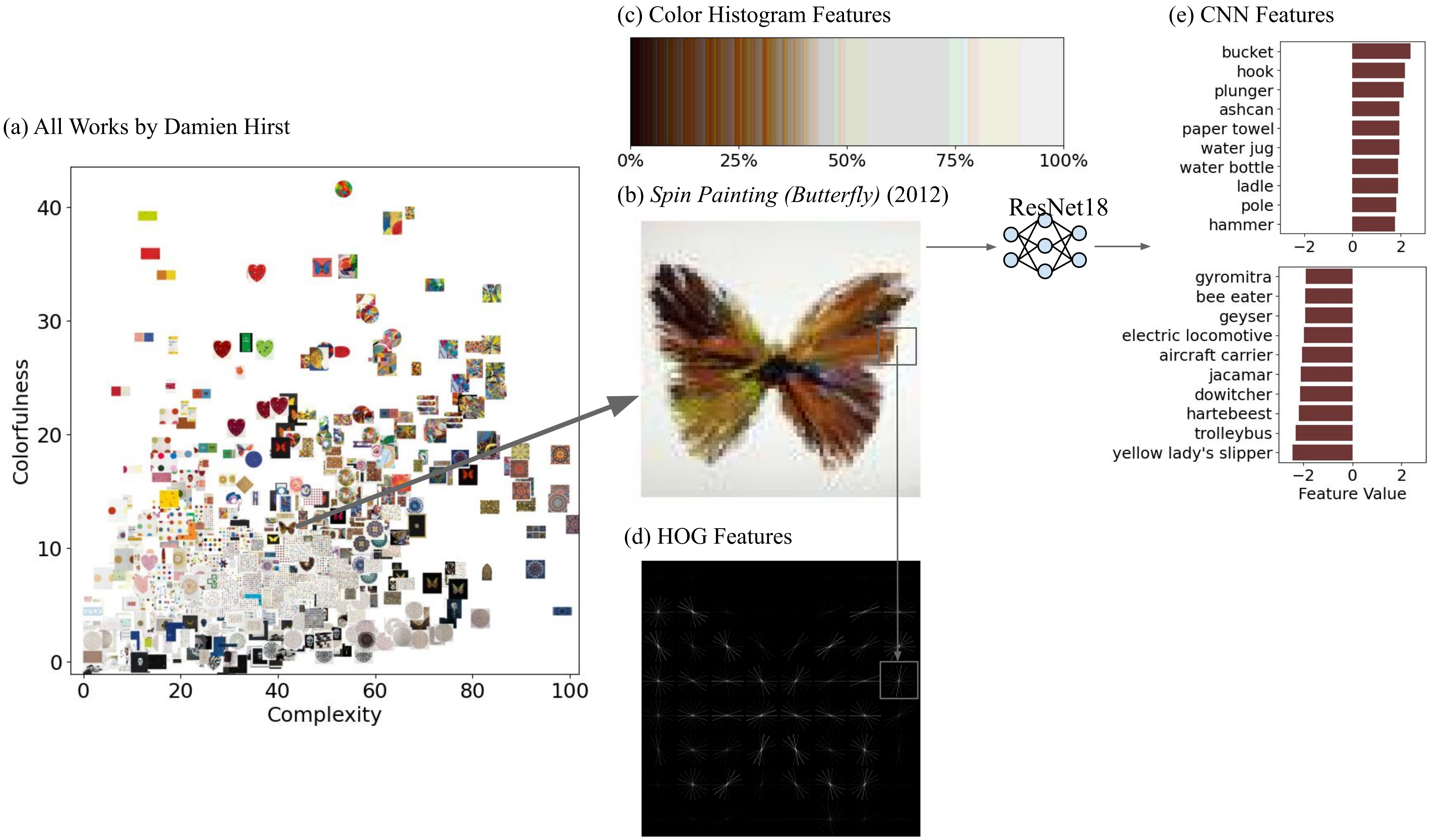
(b) *Spin Painting (Butterfly)* (2012)
(d) HOG Features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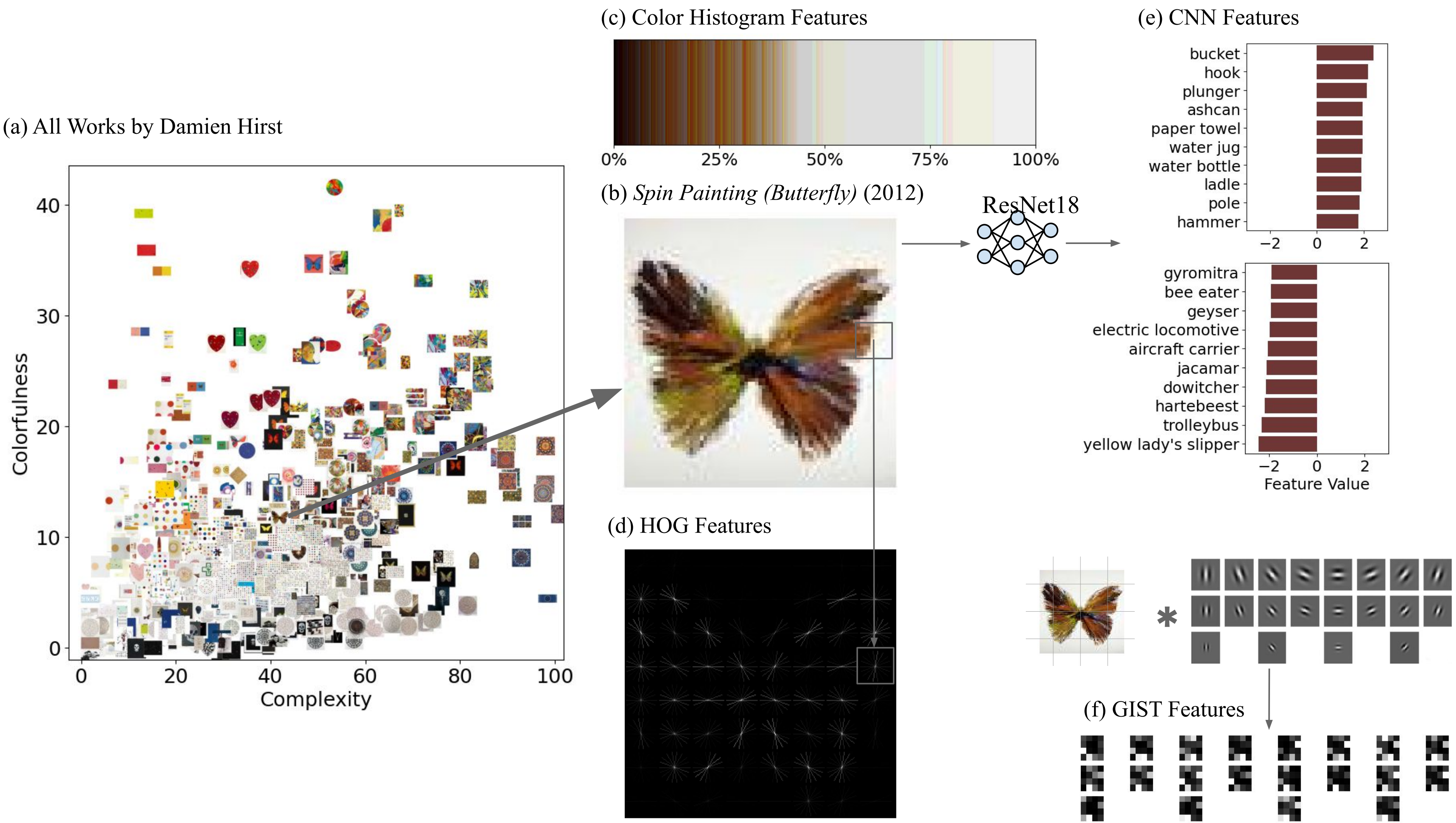
25%
50%
75%
100%
(d) HOG Features
ResNet18
(e) CNN Features
bucket
hook
plunger
ashcan
paper towel
water jug
water bottle
ladle
pole
hammer
gyromitra
bee eater
geyser
electric locomotive
aircraft carrier
jacamar
dowitcher
hartebeest
trolleybus
yellow lady's slipper
−2
0
2
Feature Value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jacamar
dowitcher
hartebeest
trolleybus
yellow lady's slipper
−2
0
2
Feature Value
(d) HOG Features
*
(f) GIST Features

Visual Features to Predictions

That leaves us with 8971 numbers to describe each image. In some cases, that's more features than pixels!

To reduce redundancy, we perform principal component analysis (PCA) to summarize that information in 100 features.

We then predict price using the XGBoost regression model, which we will discuss in more detail shortly.

Model	Price (Test set R^2)
Baseline (mean regressor)	-0.002
XGBoost (visual features)	0.397

Without metadata information, are able to achieve R^2 score of 0.397.

While these features are useful, they do not explain most variation in prices.

Model	Price (Test set R^2)
Baseline (mean regressor)	-0.002
XGBoost (visual features)	0.397
XGBoost (metadata features)	**0.733**
XGBoost (visual+metadata features)	0.713
XGBoost (metadata+ prof. est.)	**0.919**
XGBoost (visual+metadata+ prof. est.)	0.917

Metadata features are much more effective!

In fact, with metadata, visual features cease to be helpful, reducing the score both with and without professional estimates.

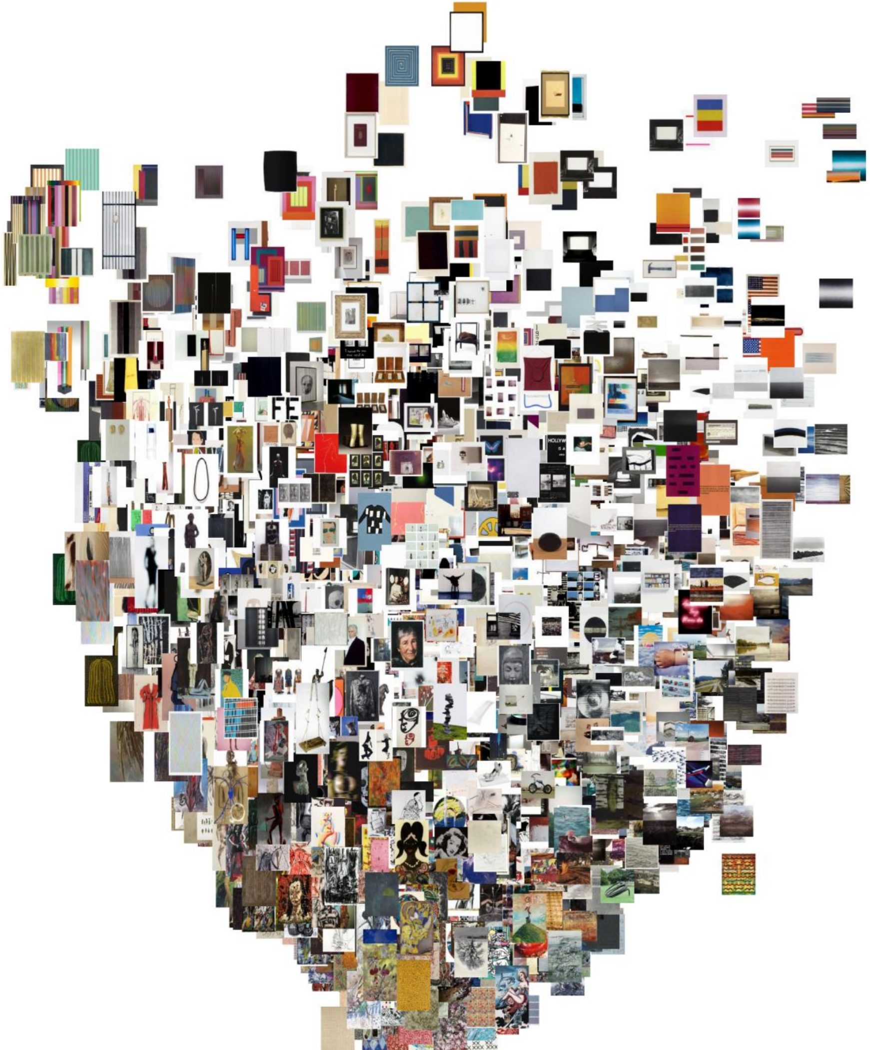
This is a really reductive way to look at art!

Art exists in many contexts

but this sort of method only consider it in the purely visual context of our dataset

and it only reaches the formal level, considering arrangements of lines and colors, and doesn't pretend to access meaning or feeling in any way

But that's still good enough to explain almost 40% of variation in price.



Buying an Artist:
Metadata Analysis of Artists and Markets

How far can we predict the price,

without seeing the artwork

(or even before it's actually made)?

Features by Category: Artwork & Market

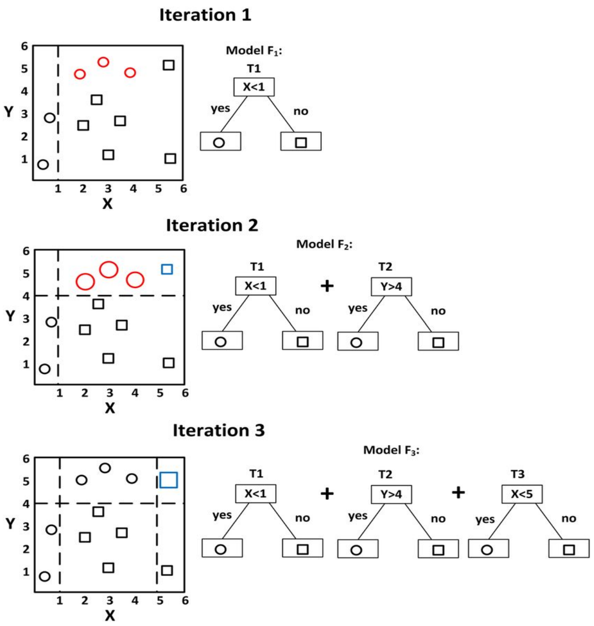
- Artwork
  (a) Width, Height, and Square-inch Size
  (b) Genre - Painting, Photography, Work on Paper, Print, and others
- Market
  (c) Year
  (d) Auction house tier
  (e) Mean / Maximum / Median Prices of Continent & Country

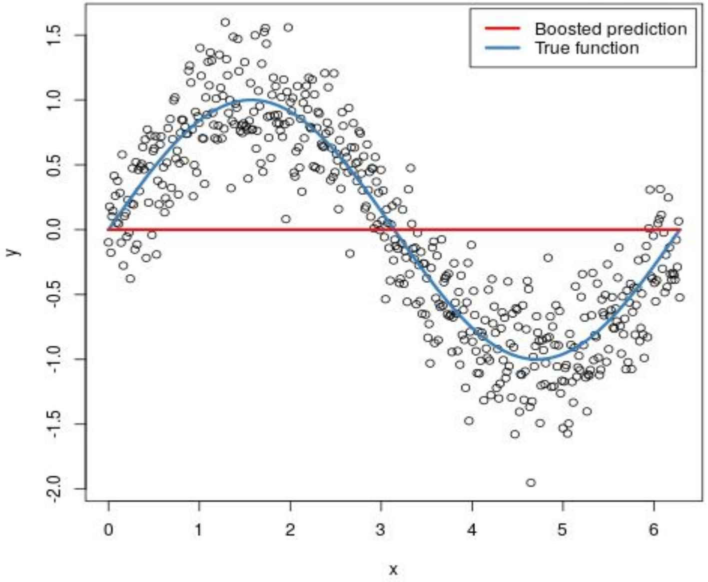
Tier	Auction Houses
1	*Christie, Sotheby,* and *Phillips* in New York or London
2	*Christie, Sotheby,* and *Phillips* in any other cities
3	*Dorotheum, Kunsthaus Lempertz, Cornette de Saint Cyr, Villa Grisebach Auktionen, Artcurial, Van Ham, im Kinsky Kunst Auktionen,* and *Ketterer Kunst*
4	All others

Features by Category: Artist

Age	Age of an artist
Gender	Gender of an artist
Education	Education level of an artist (Domestic/Abroad, Elite School or not, and Degree level)
Price - {Mean / Max / Median}	Mean / Maximum / Minimum / Median price of the artworks by an artist during the year when auction is occurred.
{Minimum / Mean / Median} price of {5 / 10} artworks	Mean / Maximum / Minimum / Median price of the artworks by an artist during the last five and ten auction transactions
{Minimum / Mean / Median} price of {5 / 10} artworks weighted by size	Size-standardized minimum / mean / median price of the artworks by an artist during the last five and ten transactions
Award	Records of art awards won by artists
Biennial	Records of participation in art fair or biennial
Ranking	Global artistic ranking of the artist as determined from U.S. and European art sources
Solo and Group Shows	Number of solo and group exhibitions for an artist, respectively
Match - Genre	Whether an artwork is identified as part of the major genre of the artist
Match - Country	Whether an artwork is sold in the working country of its artist
Private Acquisition	Number of private acquisitions of artist works by individual collectors
Public Acquisition	Number of public acquisitions by museums
Artist's working country - {Country Name}	Country where an artist is mainly working
Artist's living country - {Country Name}	Country where the auction is living

Model: Extreme Gradient Boosting (XGBoost)





Good Performance & Interpretability

Price Prediction

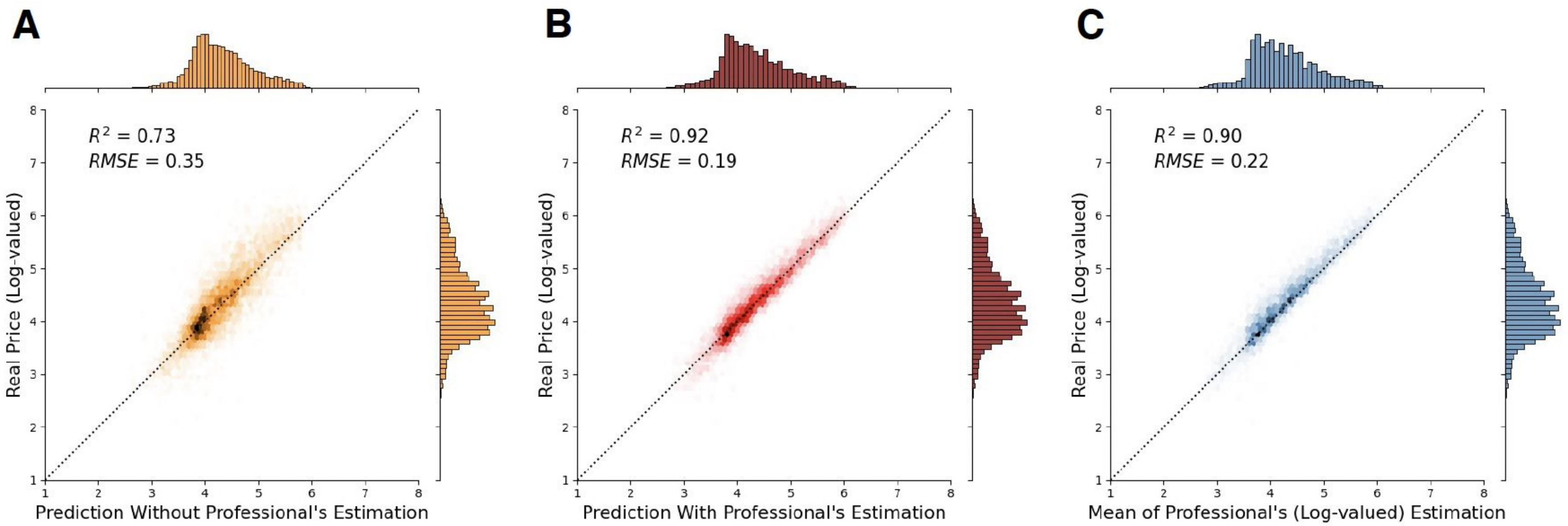
(1) Metadata, Without Professional's Estimation Information

(2) Metadata, With Professional's Estimation Information

  (a) Estimated Minimum

  (b) Estimated Maximum

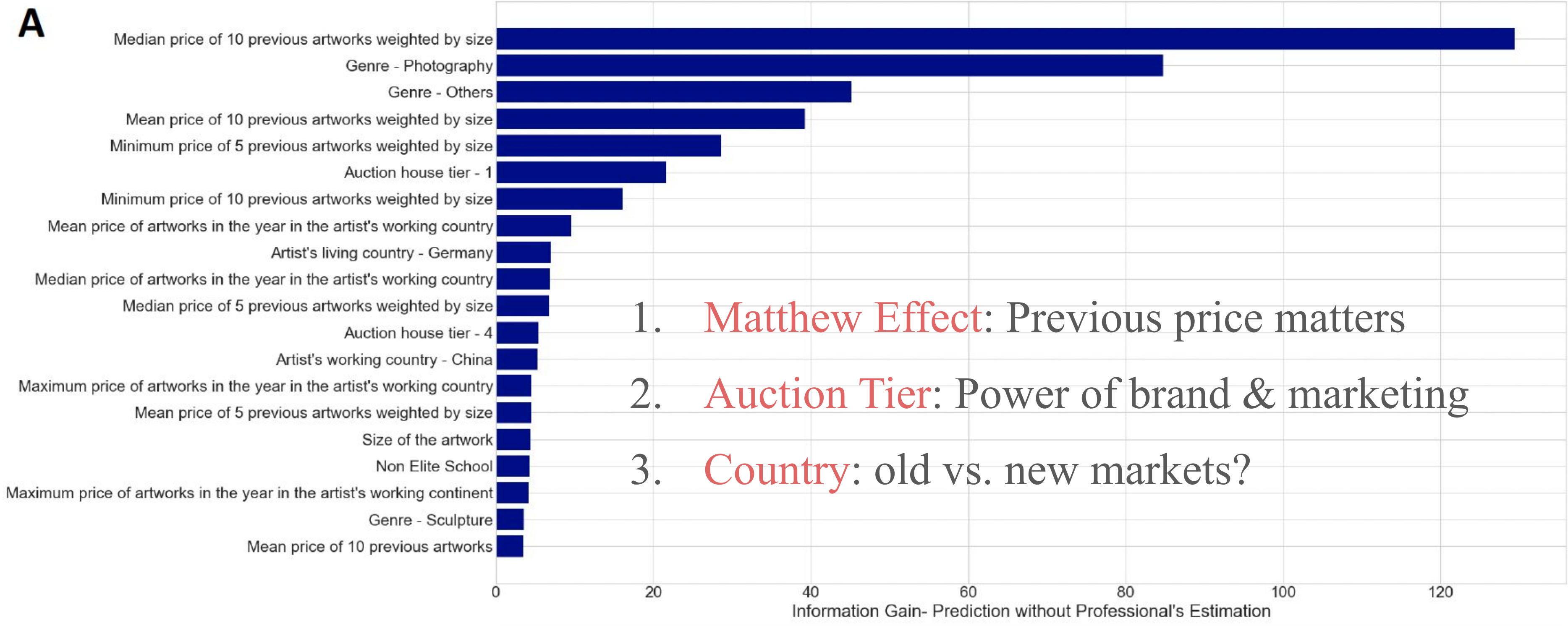
(3) Comparison with Professional's Estimation



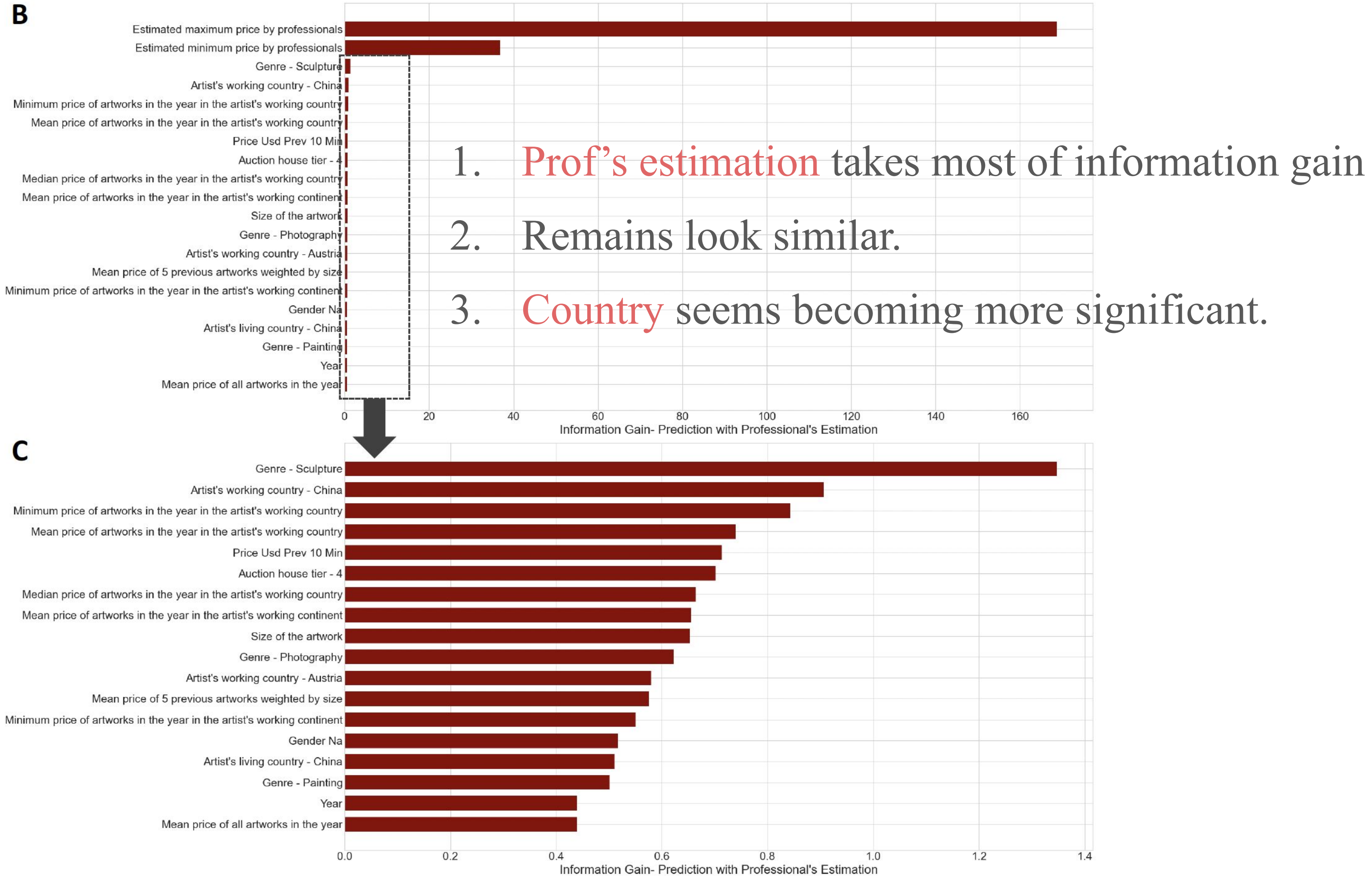
WITHOUT
Professional's Information

WITH
Professional's Information

JUST
Professional's Information



1. Matthew Effect: Previous price matters
2. Auction Tier: Power of brand & marketing
3. Country: old vs. new markets?


B
Estimated maximum price by professionals
Estimated minimum price by professionals
Genre - Sculpture
Artist's working country - China
Minimum price of artworks in the year in the artist's working country
Mean price of artworks in the year in the artist's working country
Price Usd Prev 10 Min
Auction house tier - 4
Median price of artworks in the year in the artist's working country
Mean price of artworks in the year in the artist's working continent
Size of the artwork
Genre - Photography
Artist's working country - Austria
Mean price of 5 previous artworks weighted by size
Minimum price of artworks in the year in the artist's working continent
Gender Na
Artist's living country - China
Genre - Painting
Year
Mean price of all artworks in the year
0
20
40
60
80
100
120
140
160
Information Gain- Prediction with Professional's Estimation
1. Prof's estimation takes most of information gain
2. Remains look similar.
3. Country seems becoming more significant.
C
Genre - Sculpture
Artist's working country - China
Minimum price of artworks in the year in the artist's working country
Mean price of artworks in the year in the artist's working country
Price Usd Prev 10 Min
Auction house tier - 4
Median price of artworks in the year in the artist's working country
Mean price of artworks in the year in the artist's working continent
Size of the artwork
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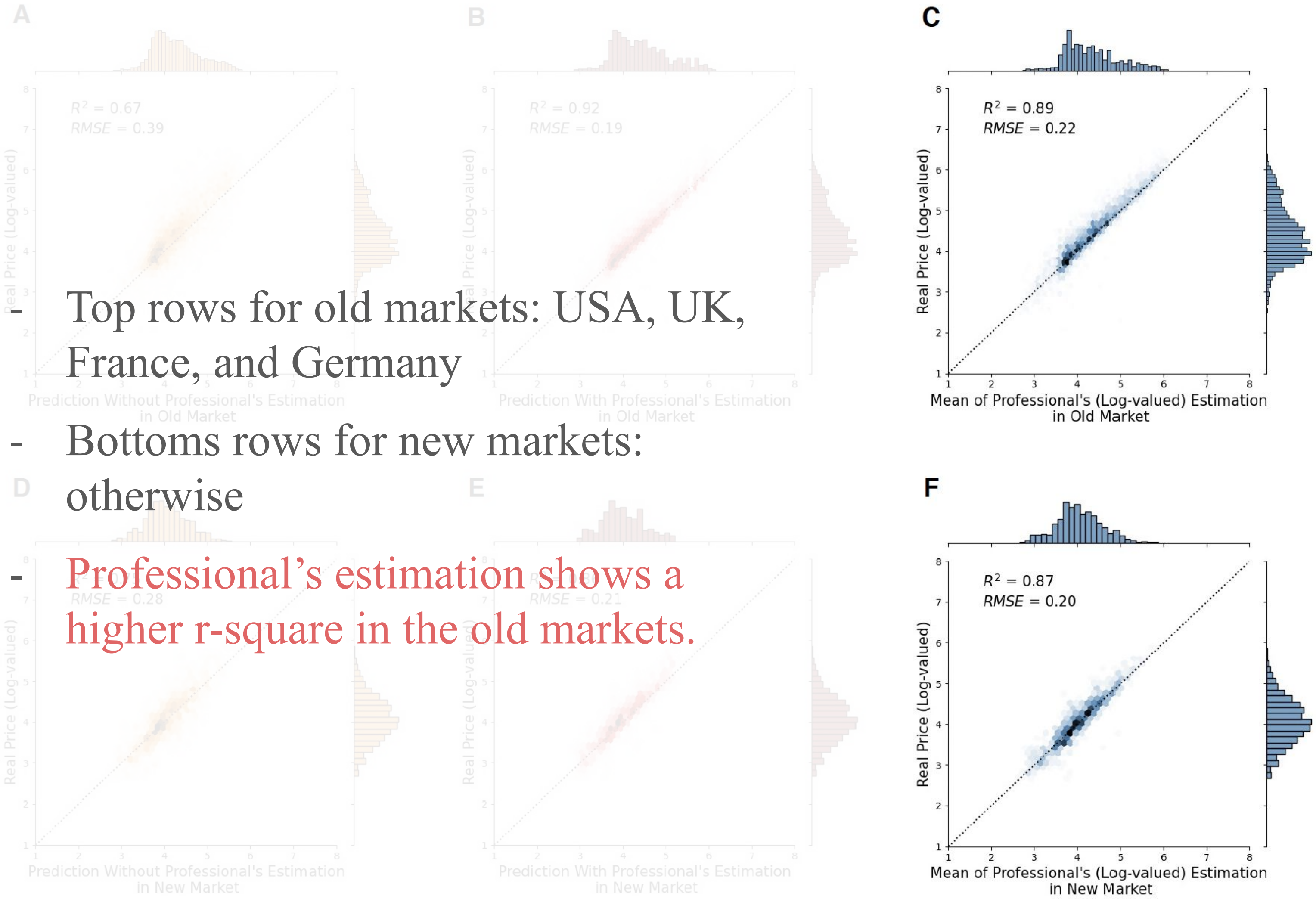
Mean price of 5 previous artworks weighted by size
Minimum price of artworks in the year in the artist's working continent
Gender Na
Artist's living country - China
Genre - Painting
Year
Mean price of all artworks in the year
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
Information Gain- Prediction with Professional's Estimation

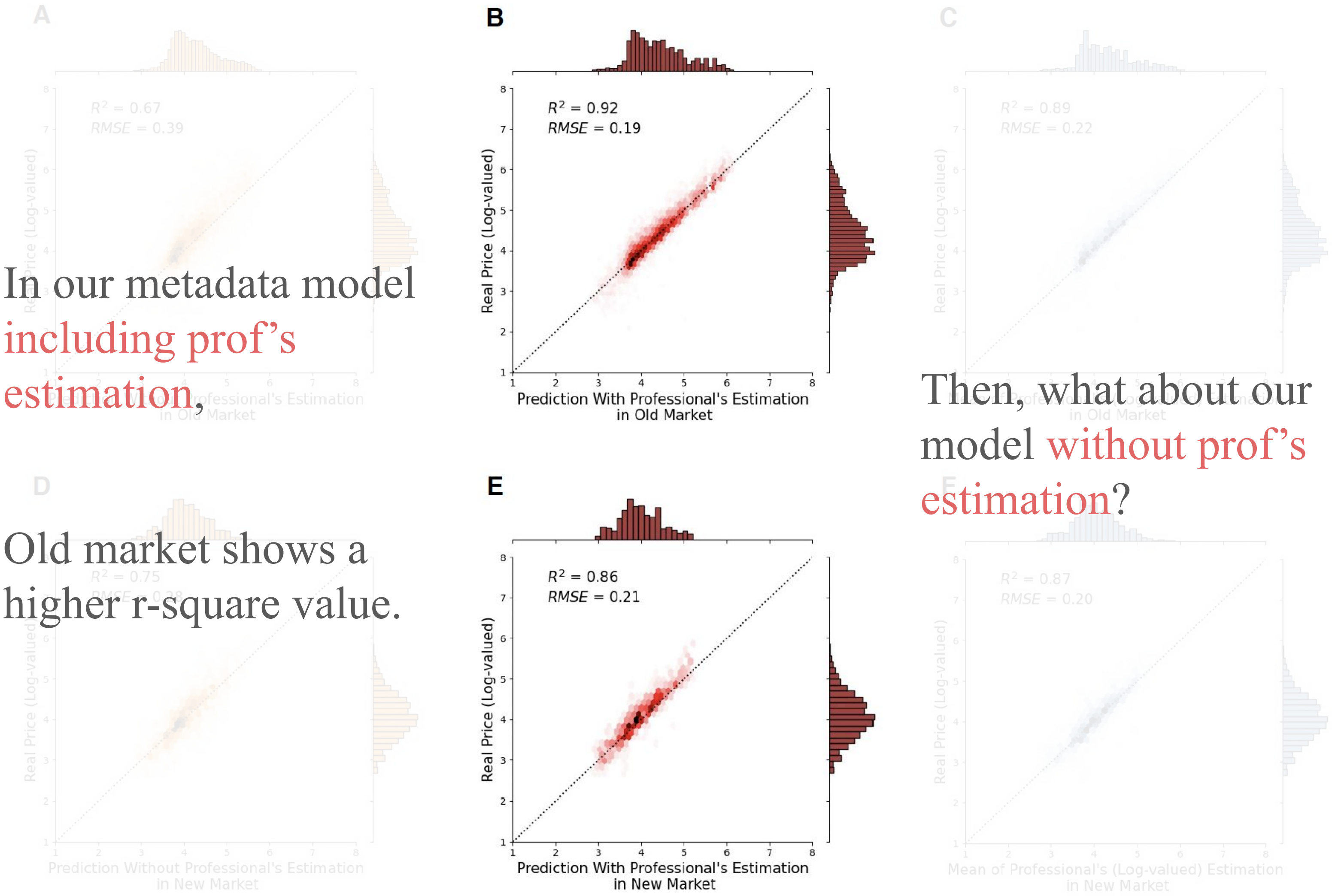


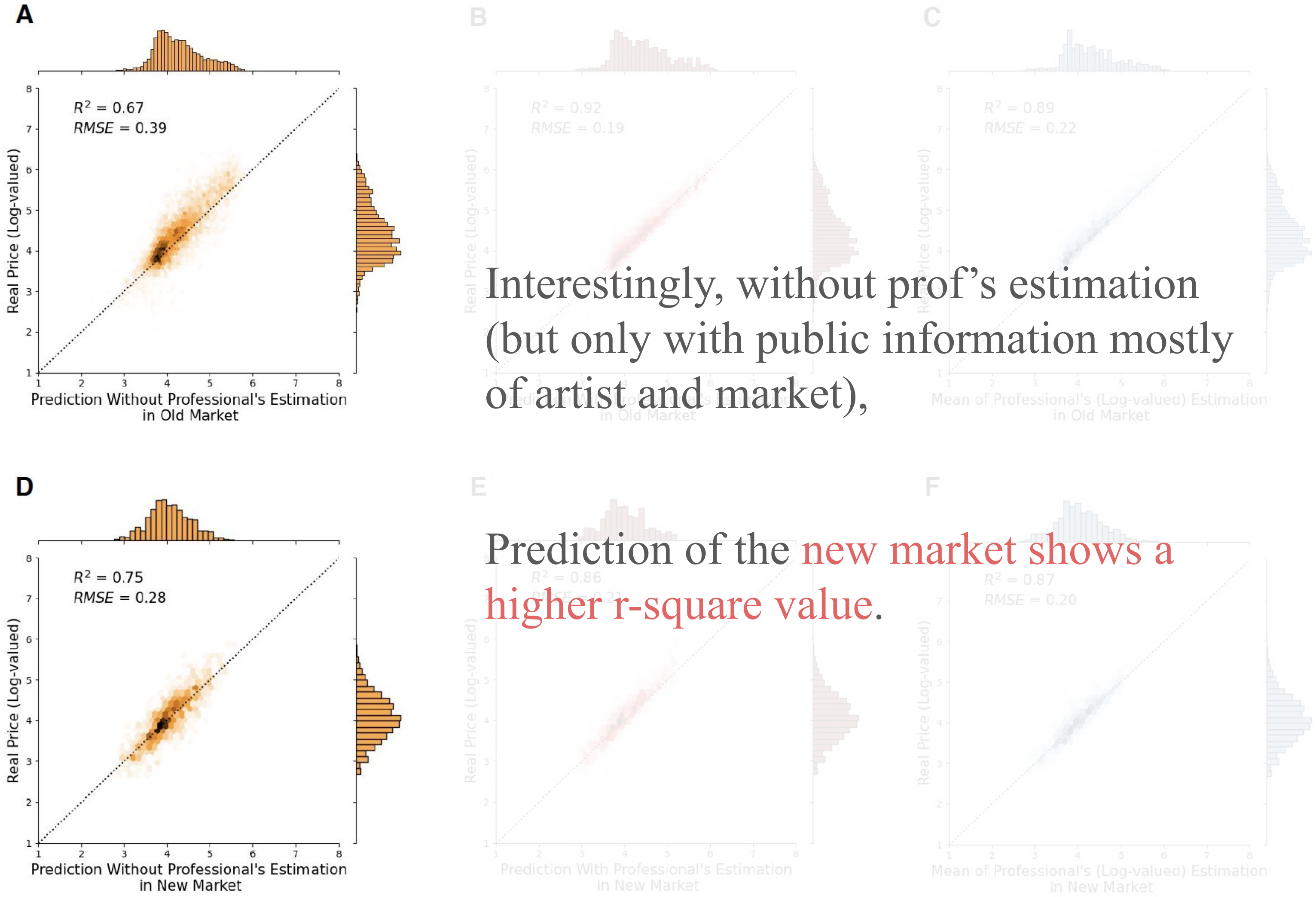
- Top rows for old markets: USA, UK, France, and Germany
- Bottoms rows for new markets: otherwise
- Professional's estimation shows a higher r-square in the old markets.

In our metadata model **including prof's estimation**,

Old market shows a higher r-square value.

Then, what about our model **without prof's estimation**?





Interestingly, without prof's estimation (but only with public information mostly of artist and market),

Prediction of the new market shows a higher r-square value.

Discussion

(1) Aesthetic Gap, the null finding of visual information

(2) Cultural consumption is highly socialized action reinforced by social mechanism.

(3) Object vs Social structures (together)

(4) The potential benefit of ML approach to complement the domain specialty (especially in new markets)