Model Visualisation

Amit Kapoor
@amitkaps

Story

"We don't see things as they are, we see them as we are."

— *Anais Nin*

The Blind Men & the Elephant

“And so these men of Indostan
Disputed loud and long,
Each in his own opinion
Exceeding stiff and strong,
Though each was partly in the right,
And all were in the wrong.”

— *John Godfrey Saxe*

The Elephant: Data

“Data is just a clue to the end truth”

— *Josh Smith*

The Men: Building Models

"All models are wrong, but some are useful"

— George Box

Ladder of Abstraction

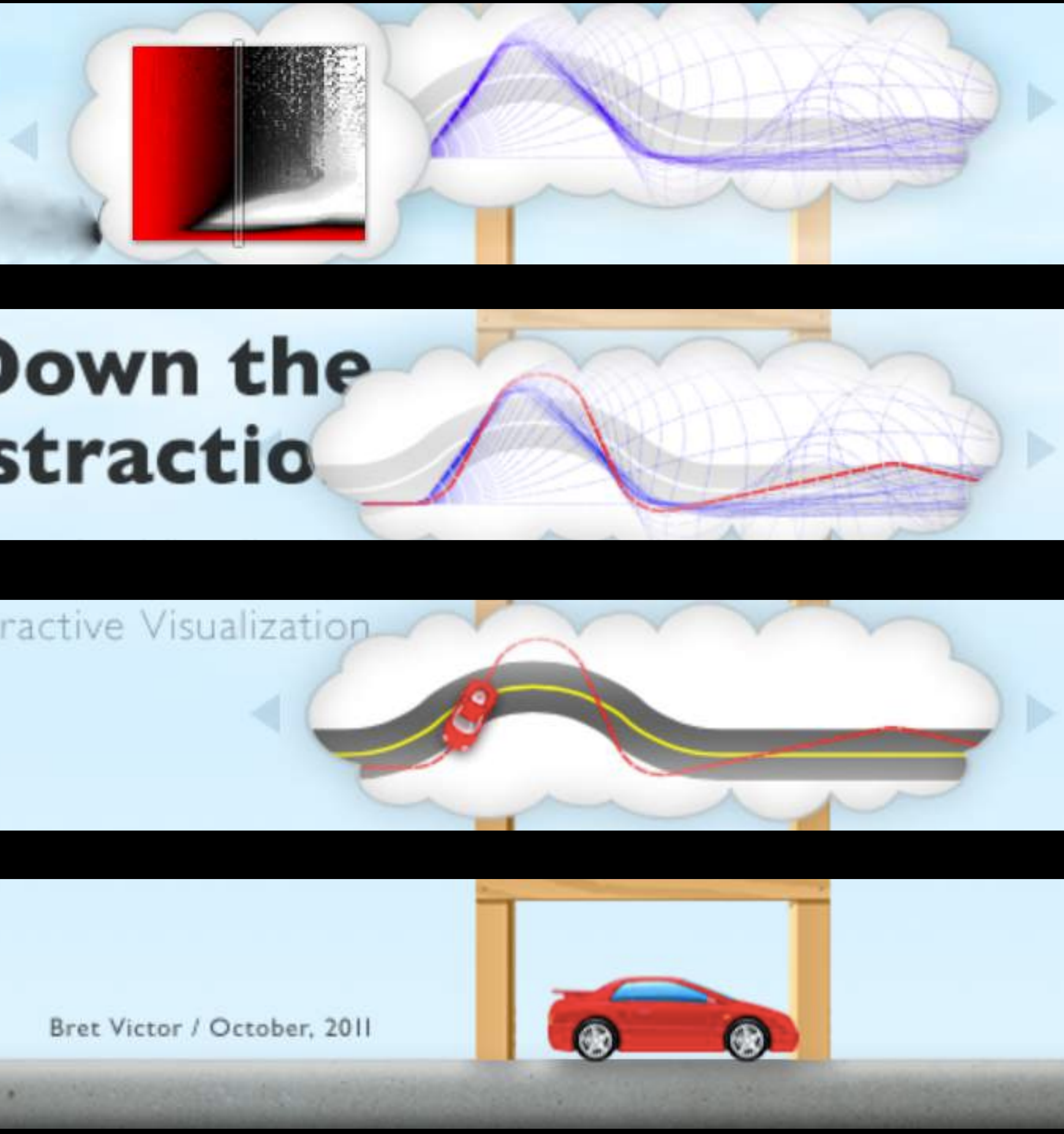
Data Abstraction

Visual Abstraction

Model Abstraction

Up and Down the Ladder of Abstractio

A Systematic Approach to Interactive Visualization



Bret Victor / October, 2011

Why Build Models?

First Level of Ignorance

"I know, what I don't know"

Why Visualise Models?

Second Level of Ignorance

"I don't know, what I don't know"

Machine Learning (ML) Speak

Data Transformation

Visual Exploration

Model Building

ML Pipeline

```
---

Data Transformation  ----  Model Building
   (Tidy Data)
        |
        |
        |
Visual Exploration
   (Data-Vis)
```

ML Pipeline++

```
Data Transformation  ----  Model Building
   (Tidy Data)               (Tidy Model)
         |                        |
         |                        |
         |                        |
Visual Exploration       Model Exploration
   (Data-Vis)                (Model-Vis)
```

Model-Vis Key Concept

Use visualisation to aid the transition of implicit knowledge in the data and your head to explicit knowledge in the model.

Model-Vis Approach

---

[0] Visualise the data space
[1] Visualise the predictions in the data space
[2] Visualise the errors in model fitting
[3] Visualise with different model parameters
[4] Visualise with different input datasets
[5] Visualise the entire model space
[6] Visualise the entire feature space
[7] Visualise the many models together

Model-Vis Examples

Regression: Small

Classification: Large p

Regression: Large n

Model-Vis Examples

Cars ($n < 50$, $p = 4$)

Digits ($n \sim 5K$, $p = 785$)

Taxi ($n \sim 10M$, $p = 20$)

Regression: Small

Cars dataset - price vs kmpl

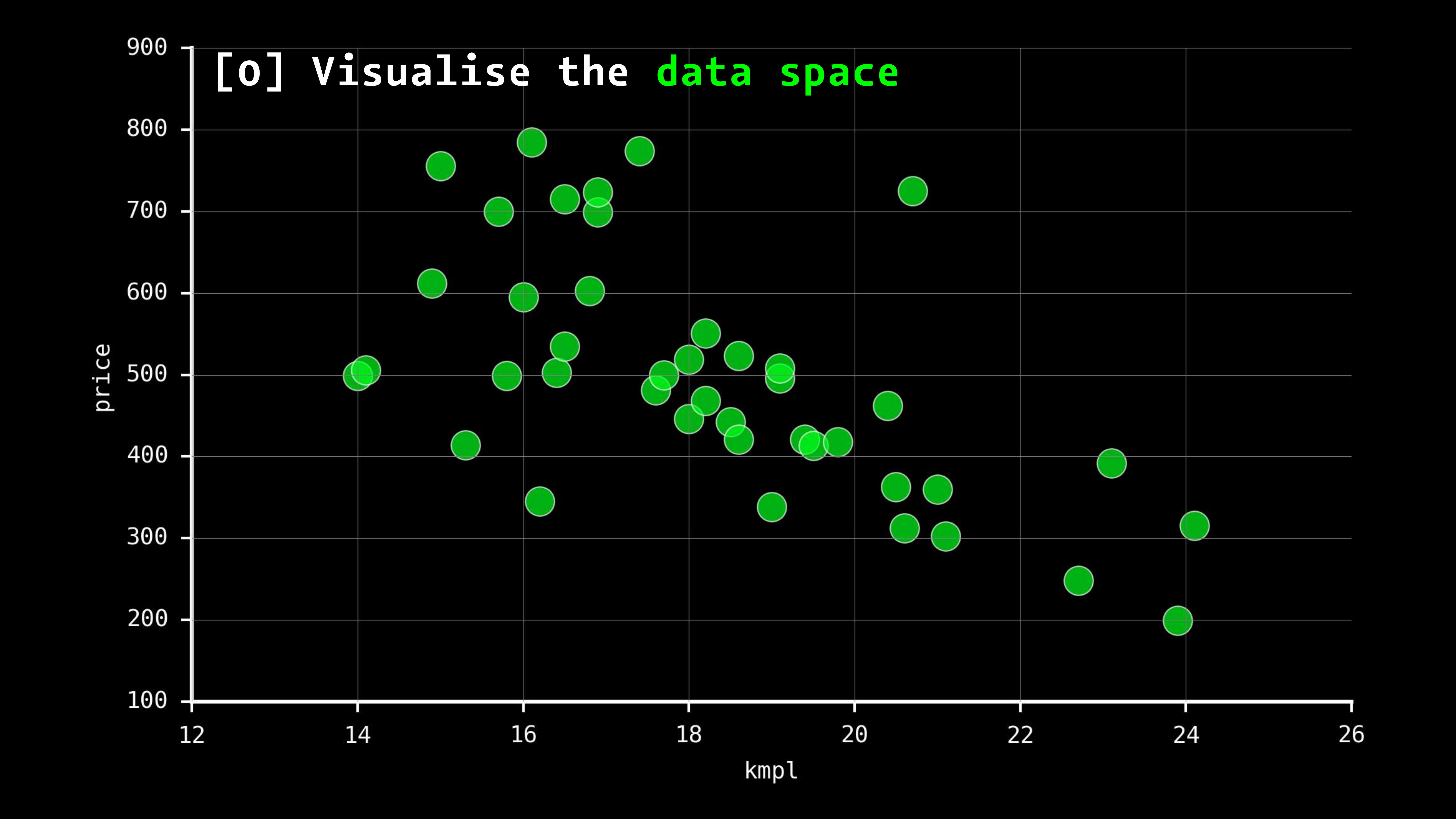
Scraped from comparison website

Refined & tidied up

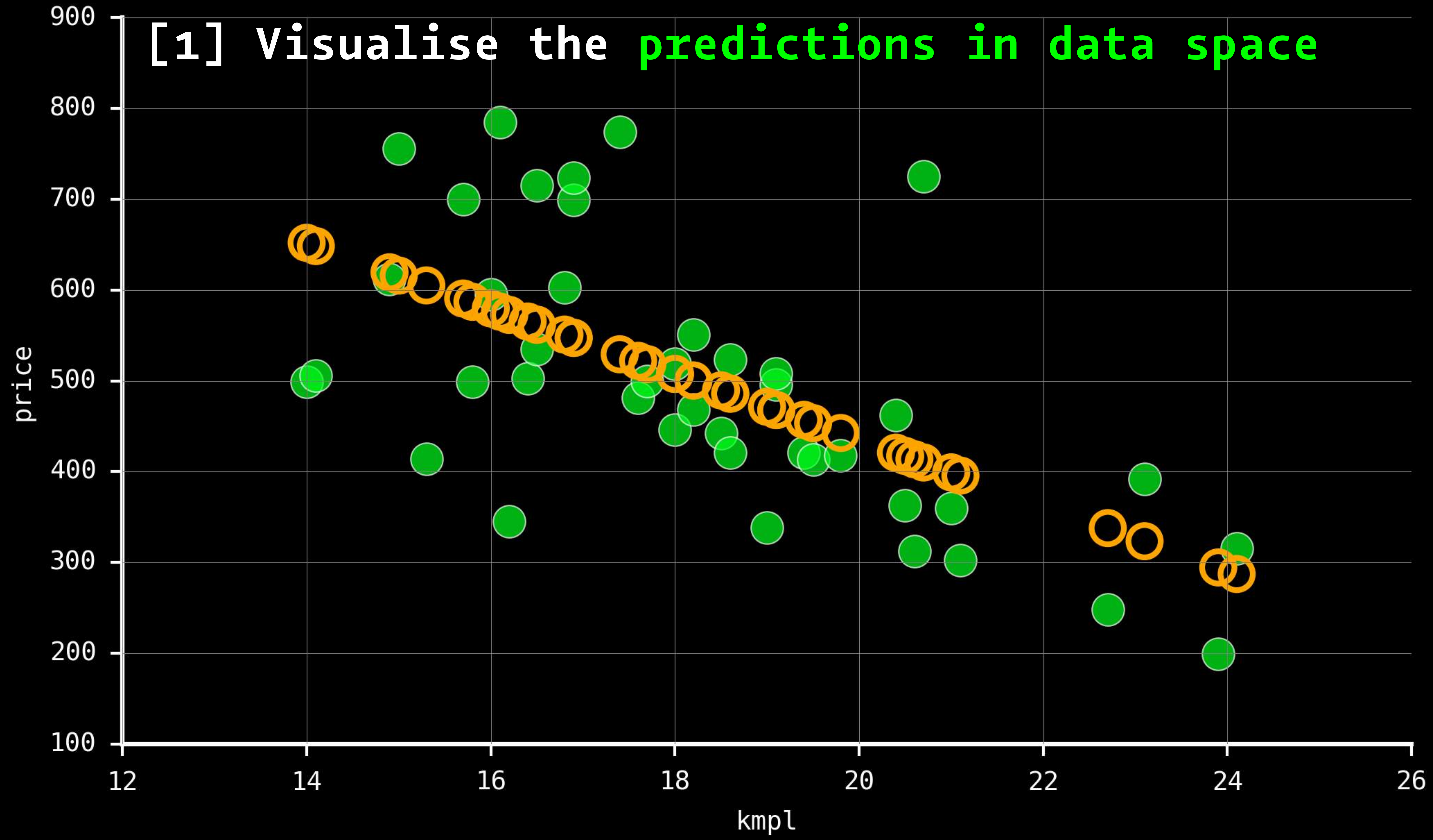
Base version for petrol cars

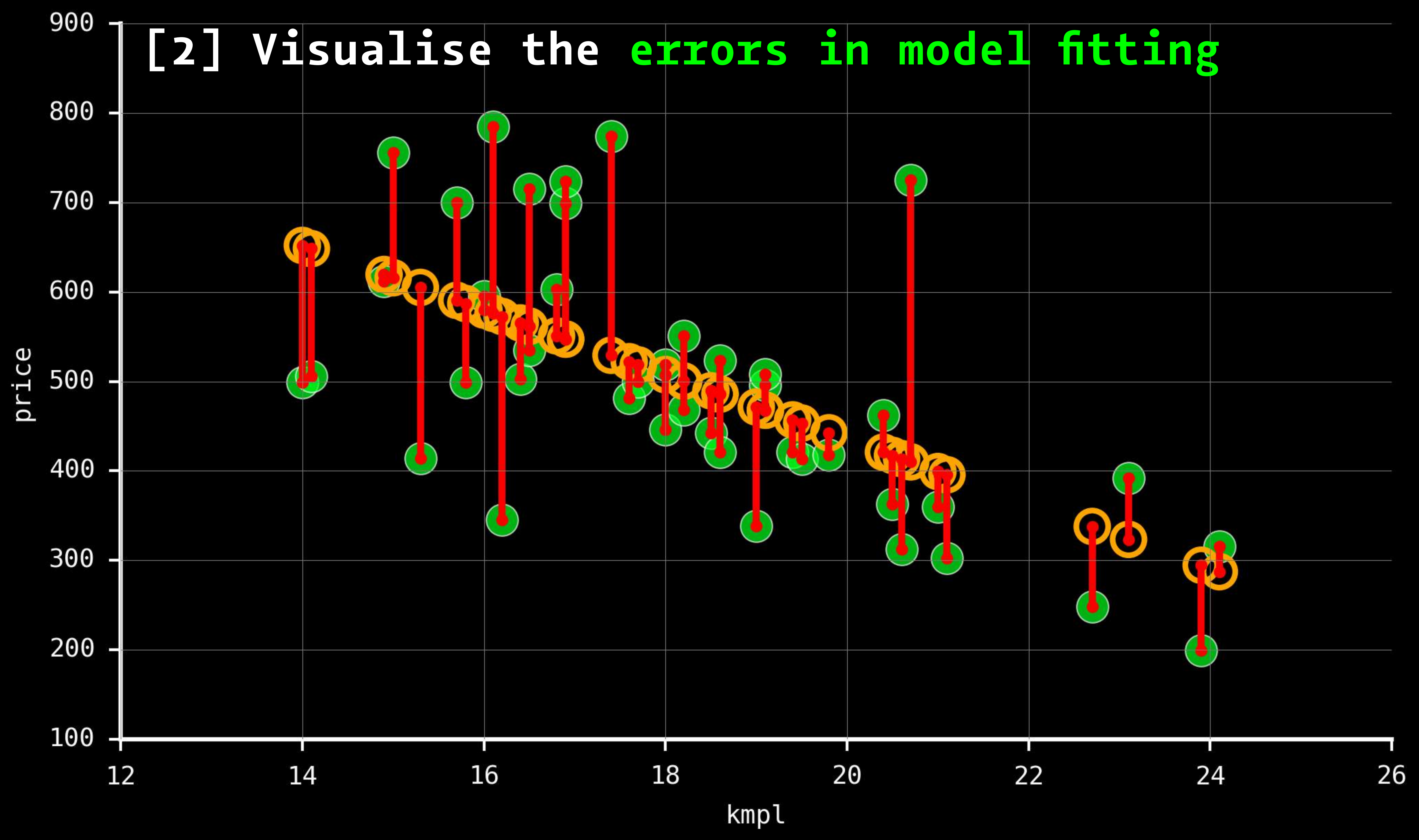
Price < ₹ 1,000K, n = 42

brand	model	price	kmpl	type	bhp
Tata	Nano	199	23.9	Hatchback	38
Suzuki	Alto800	248	22.7	Hatchback	47
Hyundai	EON	302	21.1	Hatchback	55
Nissan	Datsun	312	20.6	Hatchback	67
...	...	...	...	...	...
Suzuki	Ciaz	725	20.7	Sedan	91
Skoda	Rapid	756	15.0	Sedan	104
Hyundai	Verna	774	17.4	Sedan	106
VW	Vento	785	16.1	Sedan	104

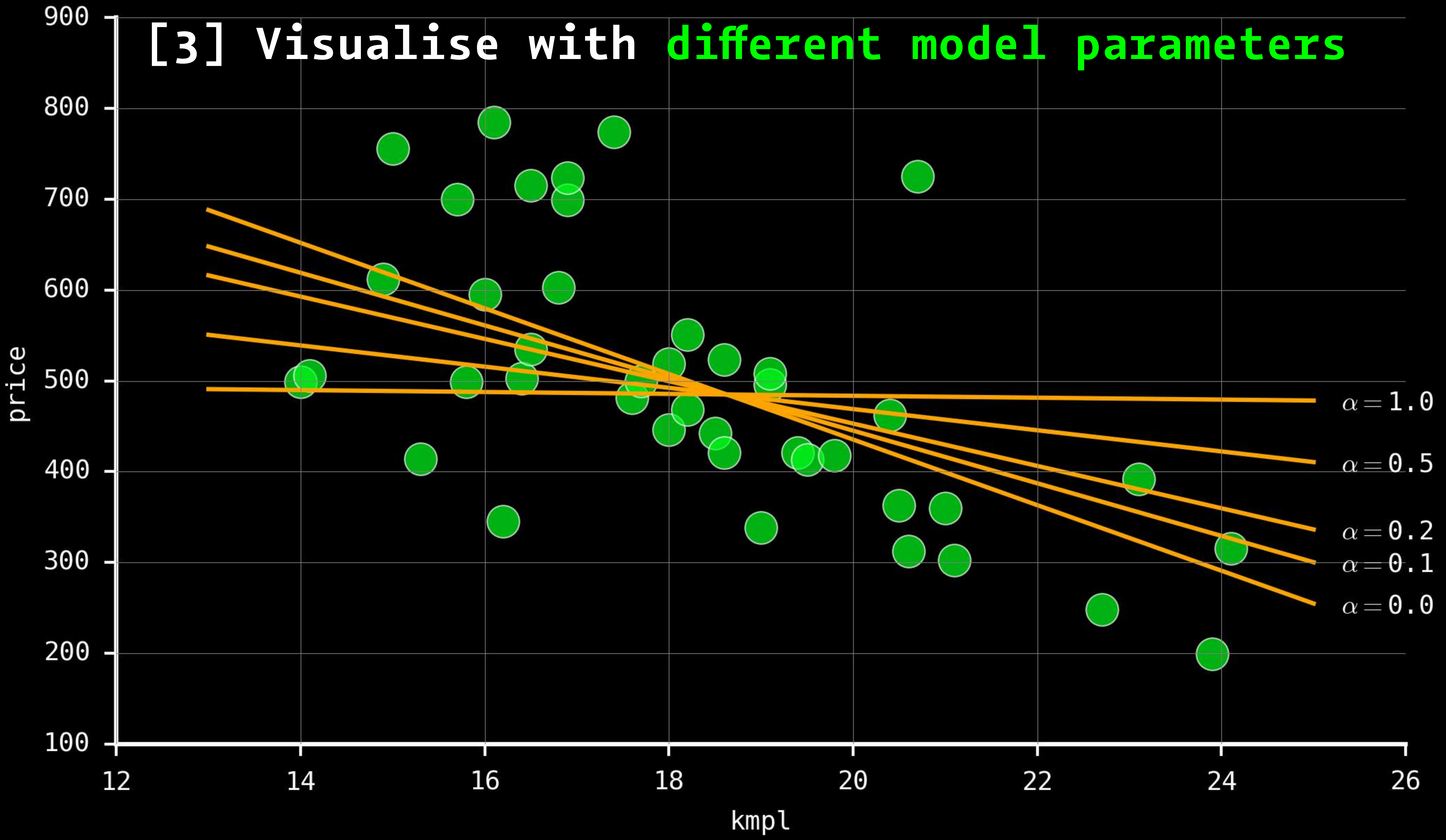

[0] Visualise the data space
price
kmpl
900
800
700
600
500
400
300
200
100
12
14
16
18
20
22
24
26

[1] Visualise the predictions in data space

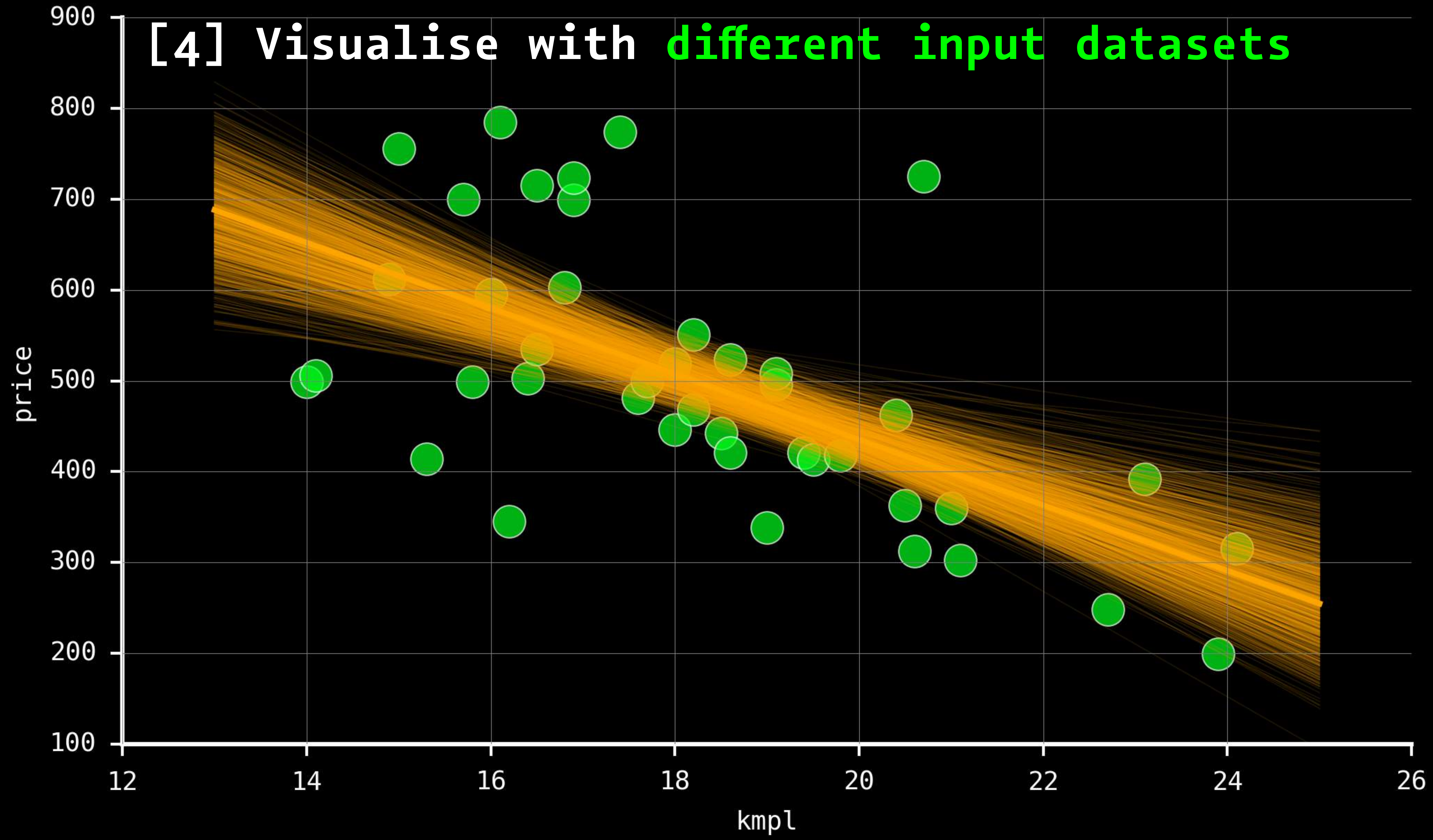



[2] Visualise the errors in model fitting
price
kmpl
900
800
700
600
500
400
300
200
100
12
14
16
18
20
22
24
26

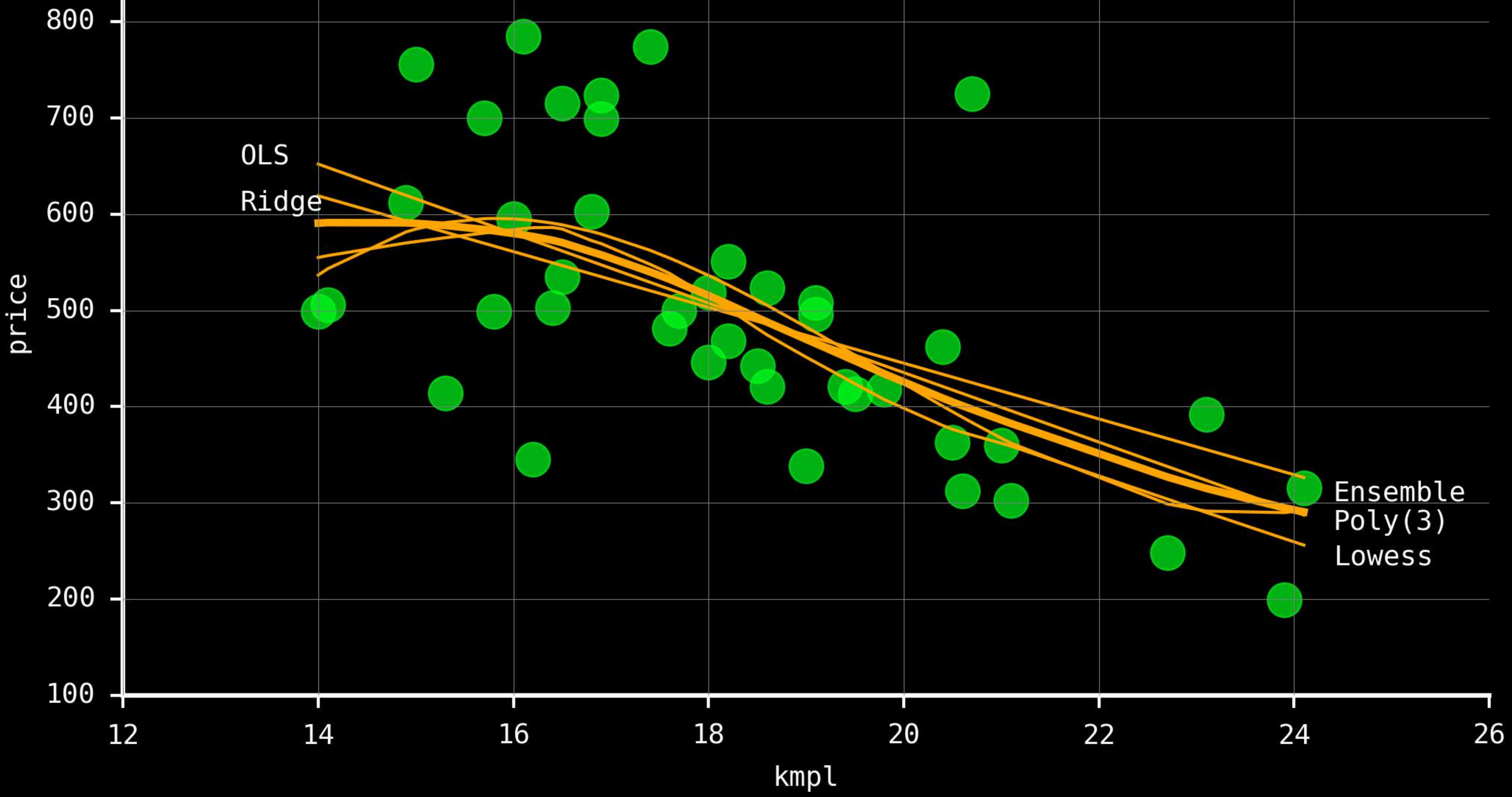
[3] Visualise with different model parameters



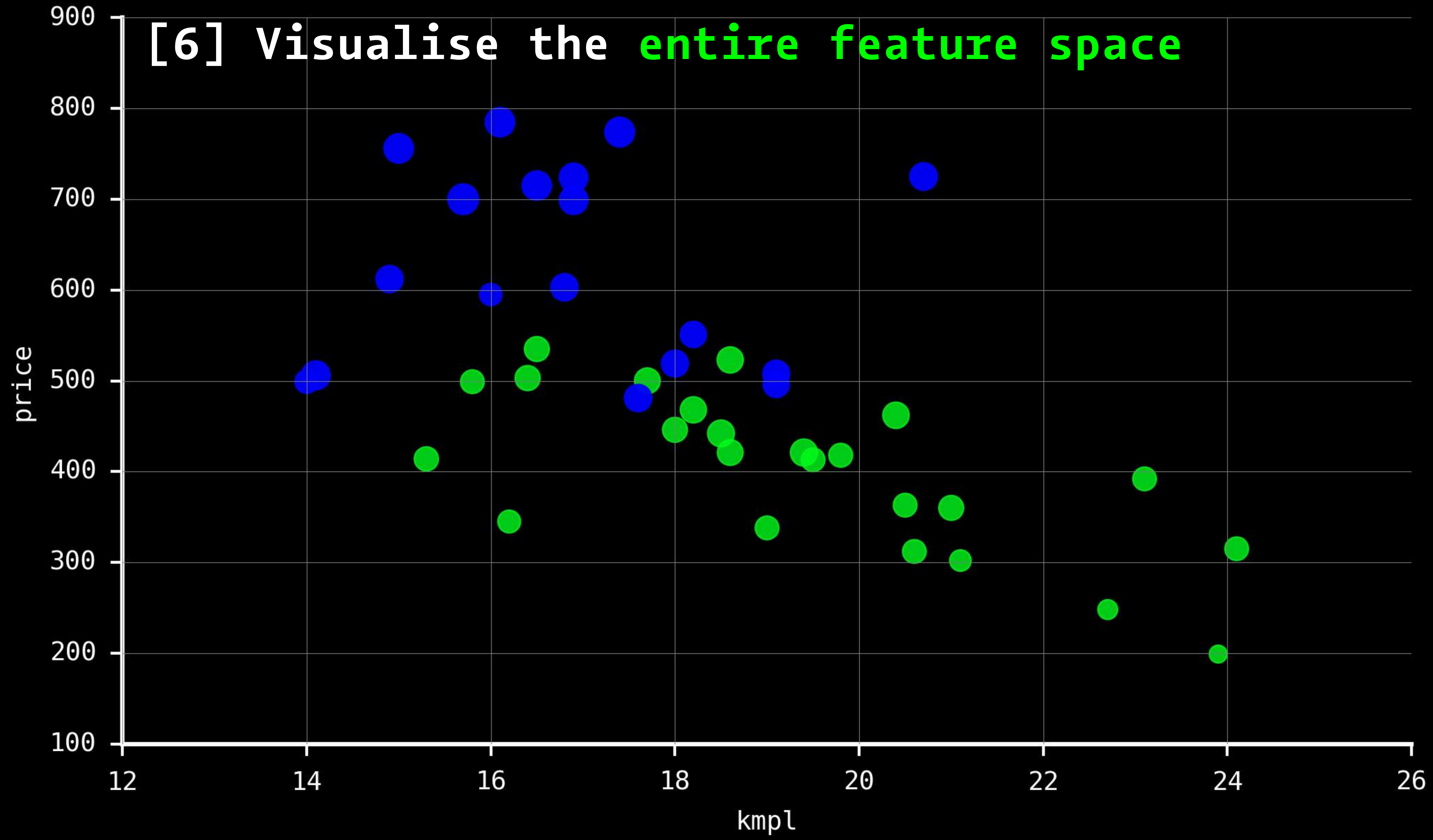
[4] Visualise with different input datasets

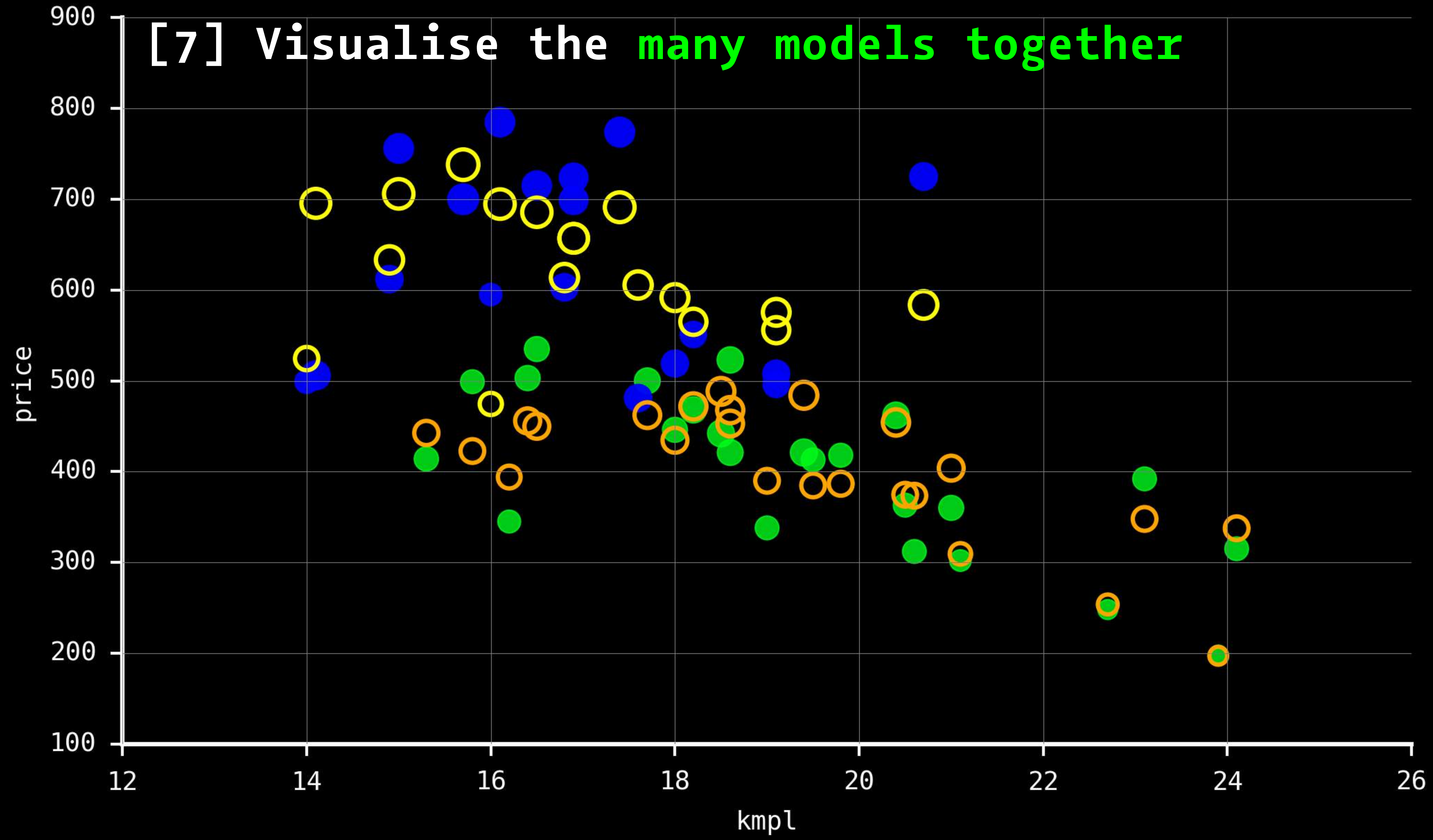


[5] Visualise the entire model space



[6] Visualise the entire feature space




[7] Visualise the many models together
900
800
700
600
500
400
300
200
100
price
12
14
16
18
20
22
24
26
kmpl

Model-Vis Approach

---

[0] Visualise the data space
[1] Visualise the predictions in the data space
[2] Visualise the errors in model fitting
[3] Visualise with different model parameters
[4] Visualise with different input datasets
[5] Visualise the entire model space
[6] Visualise the entire feature space
[7] Visualise the many models together

Model-Vis & ML Approach

---

[0] DATA VIS: the data space
[1] PREDICTION: the predictions in the data space
[2] VALIDATION: the errors in model fitting
[3] TUNING: with different model parameters
[4] BOOTSTRAP: with different input datasets
[5] ENSEMBLE: the entire model space
[6] FEATURE ENGG: the entire feature space
[7] N-MODELS: the many models together

Move through Layers

Iterative, not linear

Up and Down, not lateral

Complementary, not exclusive

p/n/N Model-Vis challenge

---

p -- High dimensional data

n -- Large and big data

N -- Multiple models

Classification: 2 Class

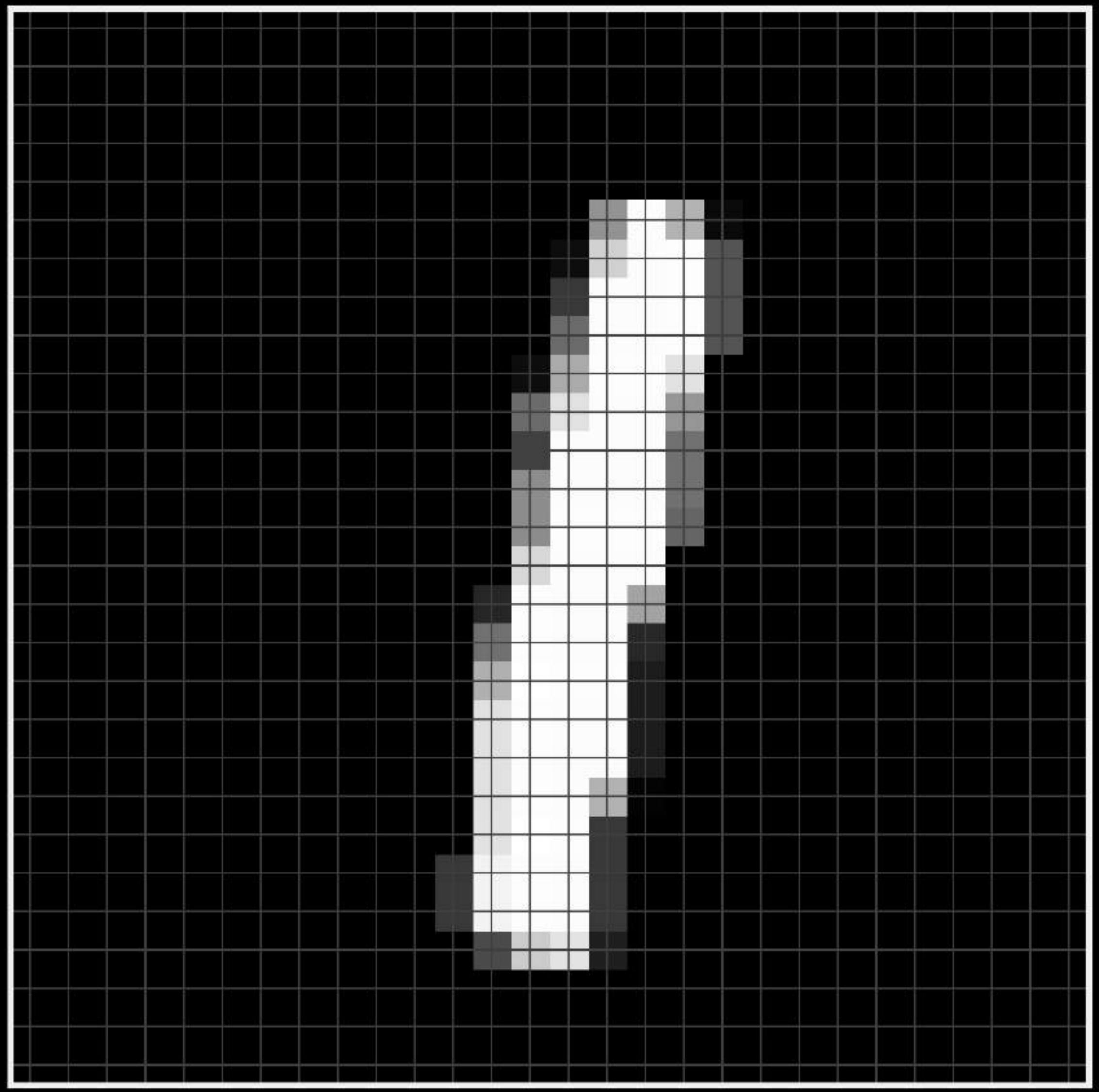
MNIST - digit recognition

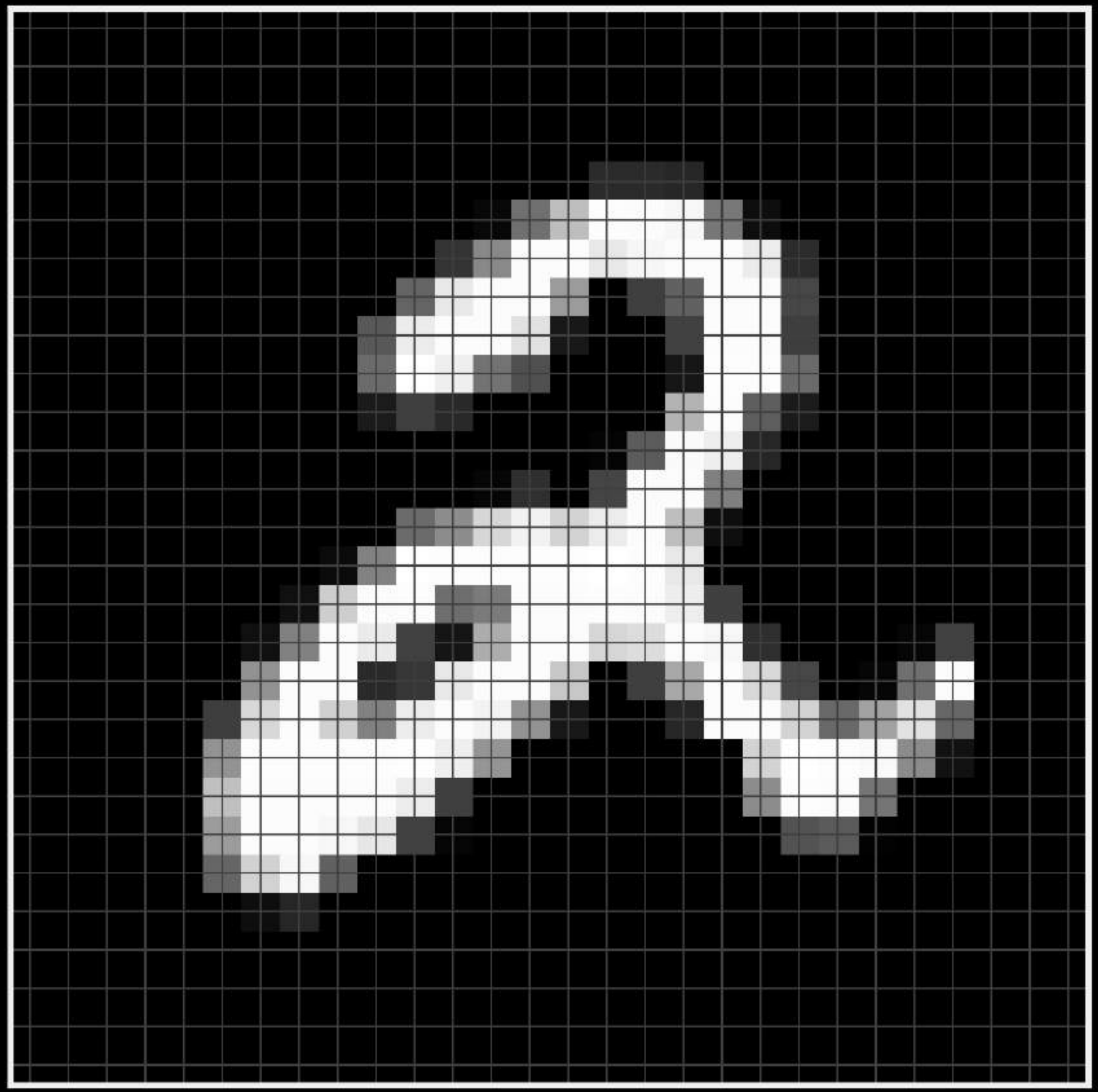
Reduced to 2-class: 1 and 2

p = 784, 28 x 28 gray pixel map

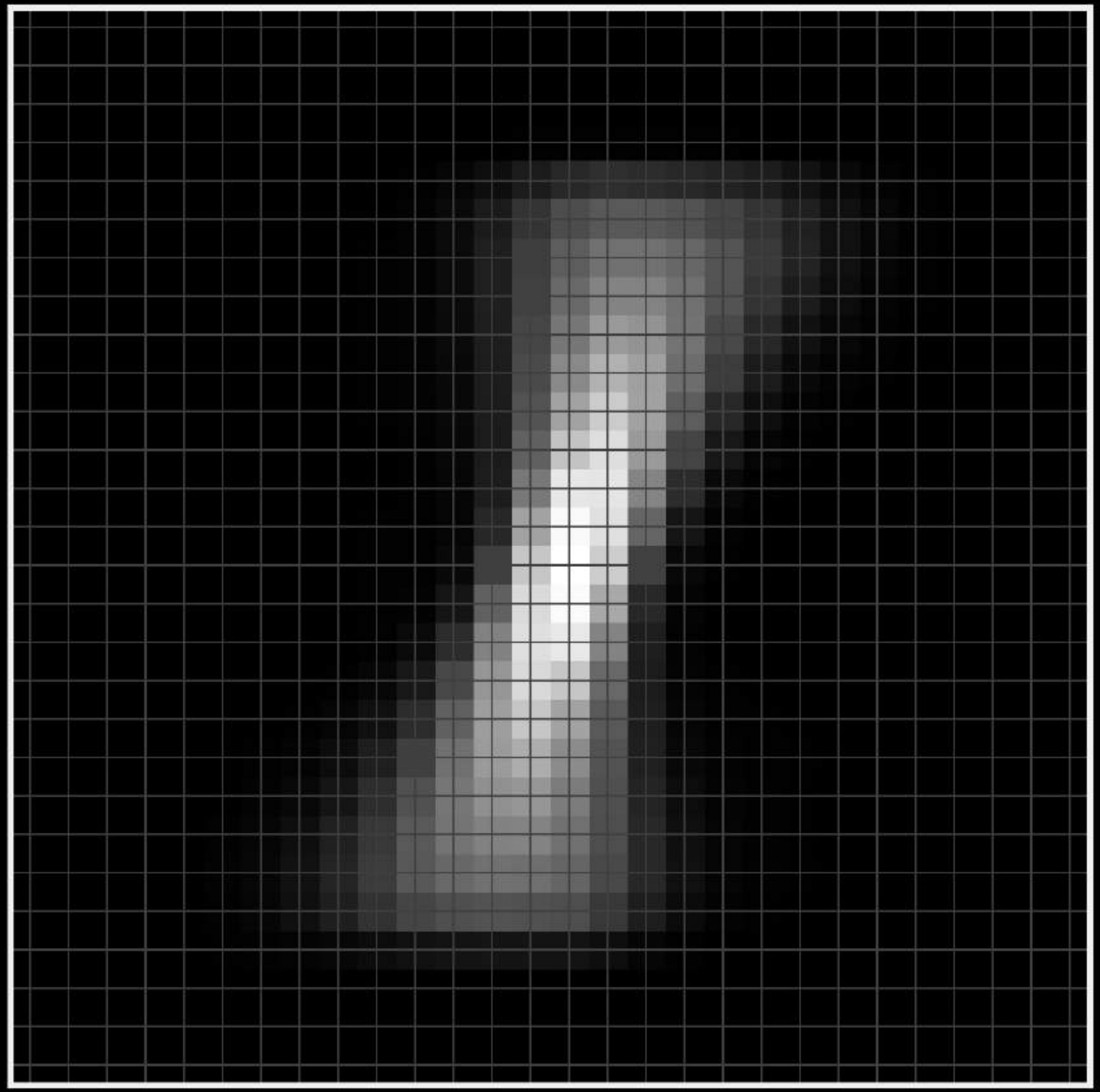
n > 5000

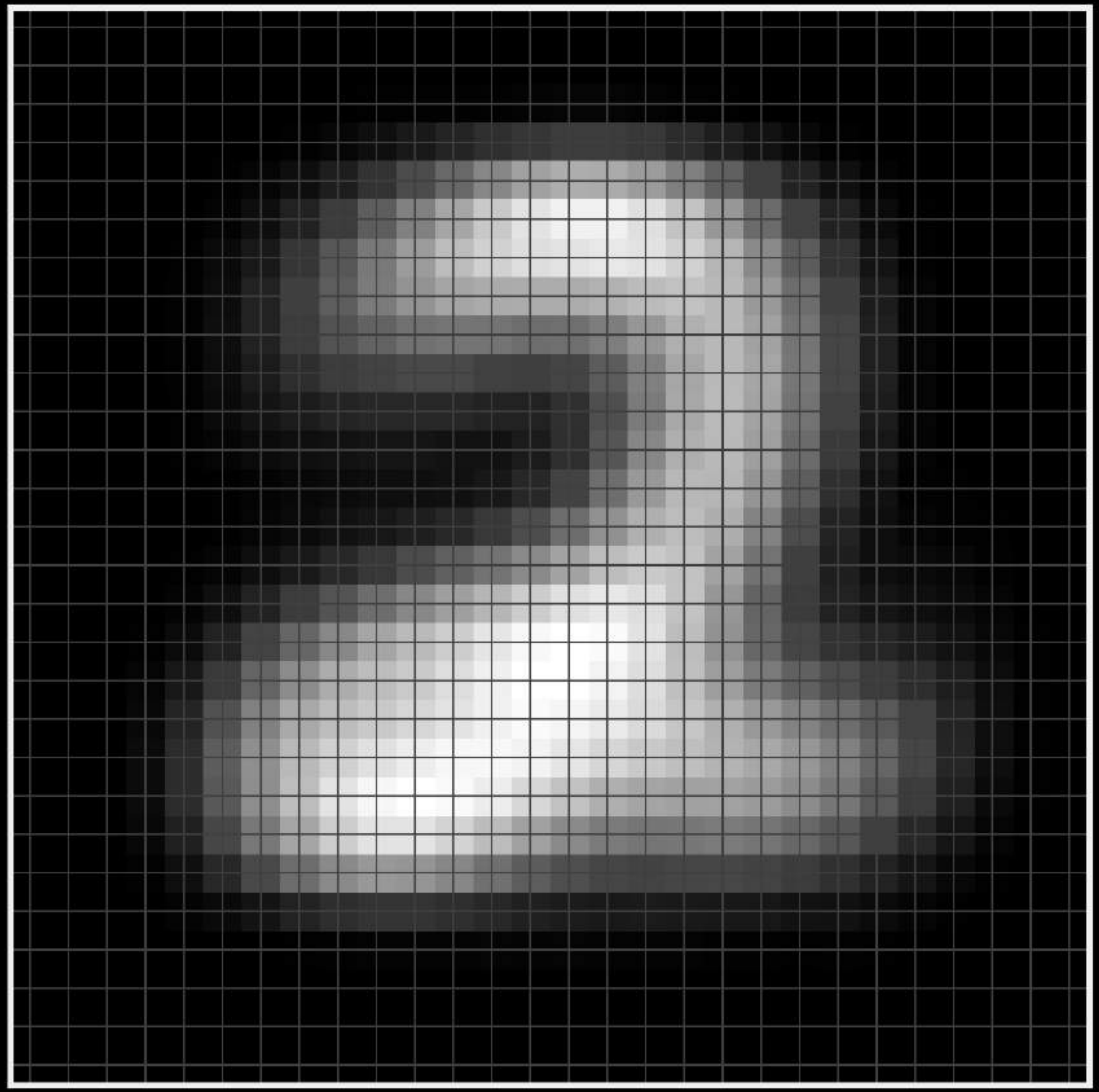
MNIST dataset: Examples of number 1 and 2



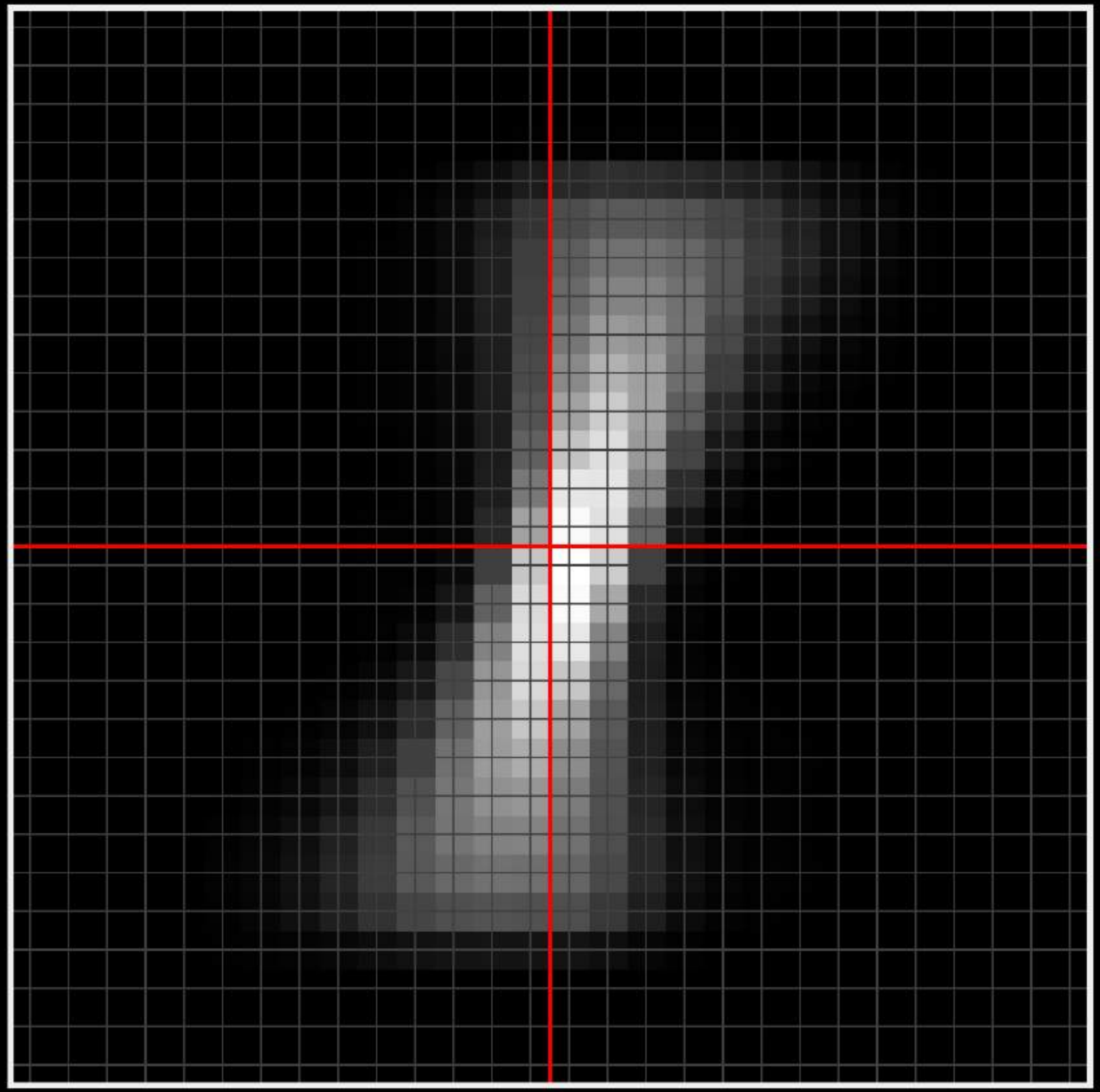


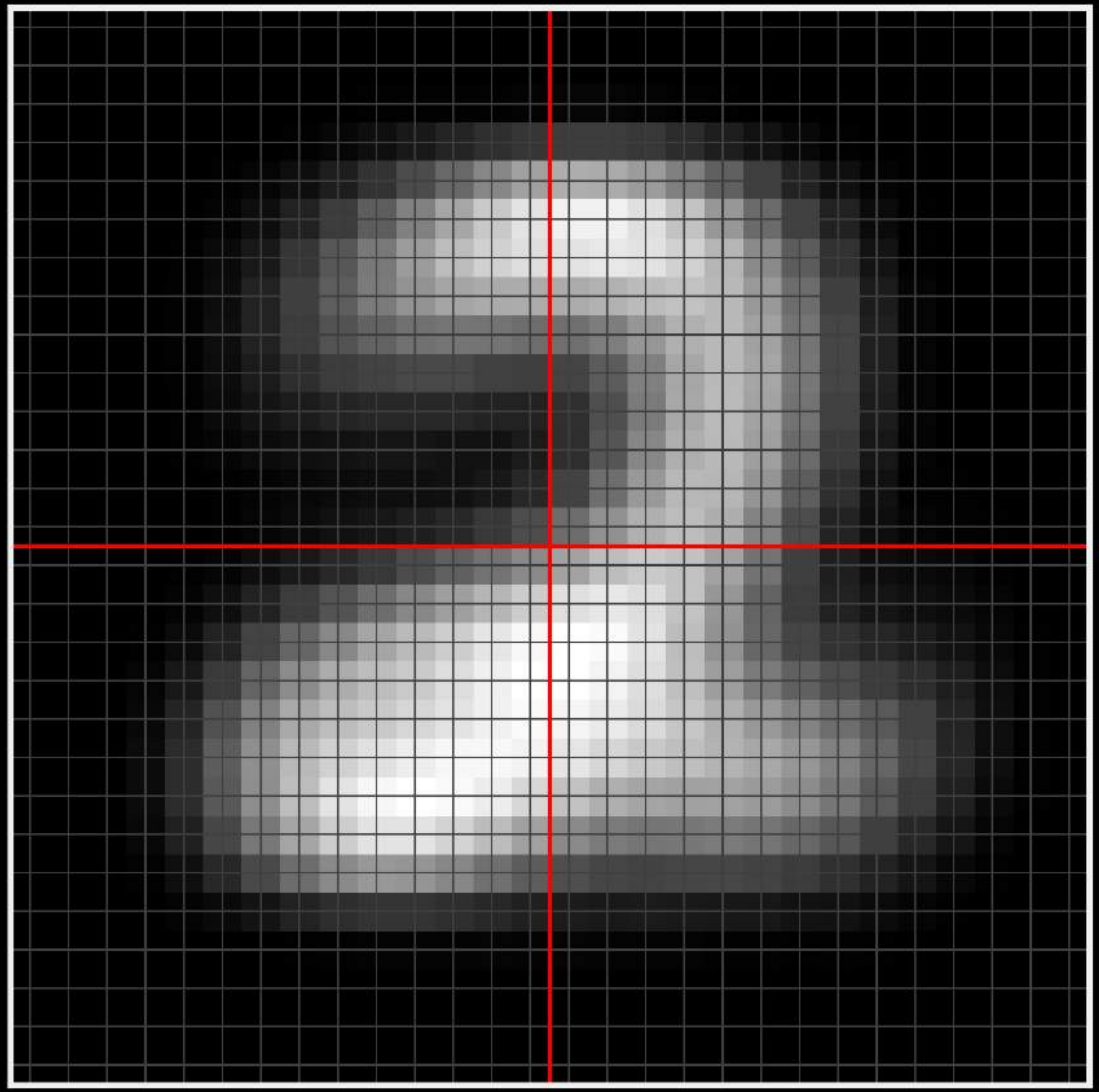
Visualise the data space

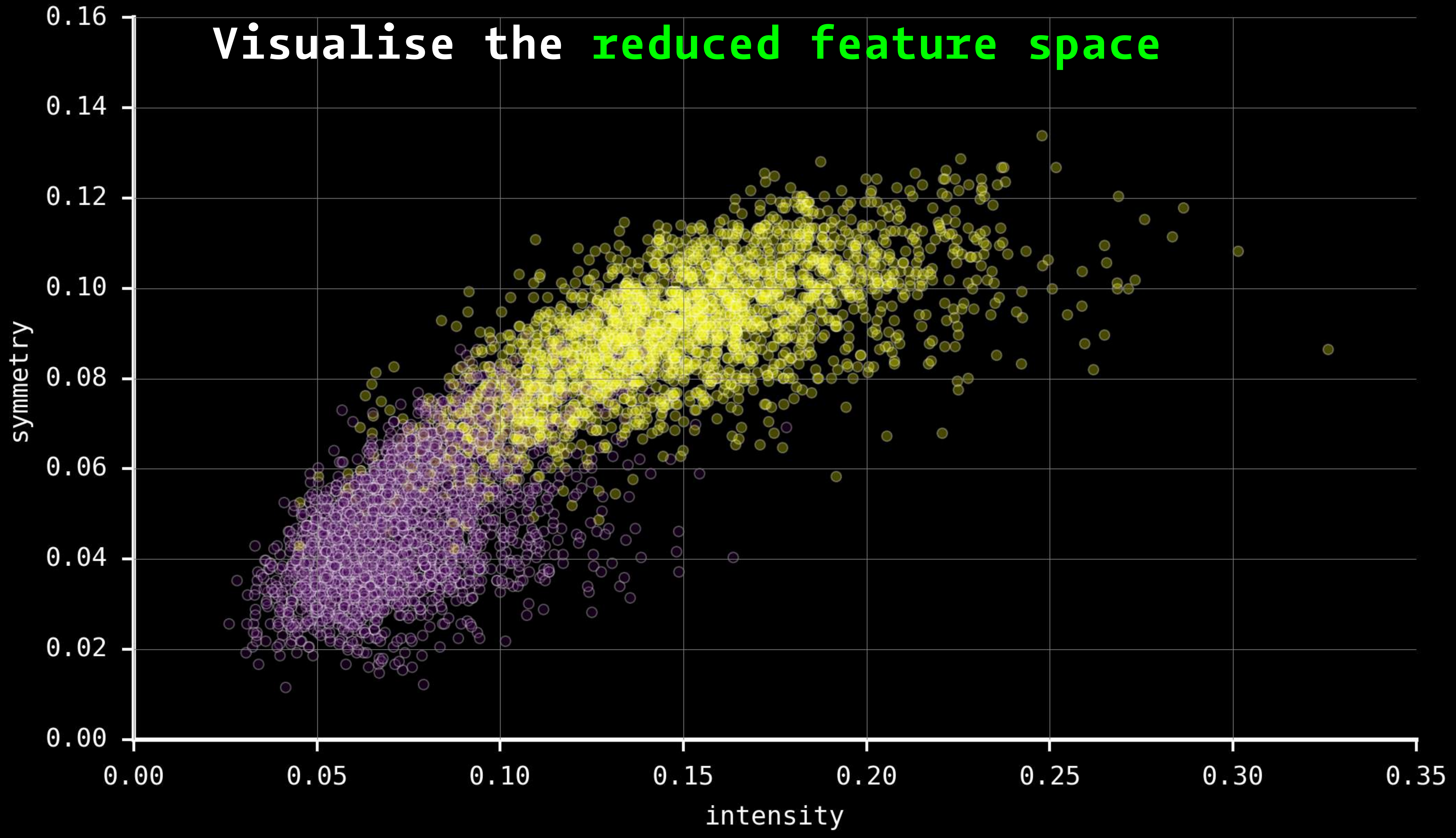




Identify the features - Symmetry & Intensity

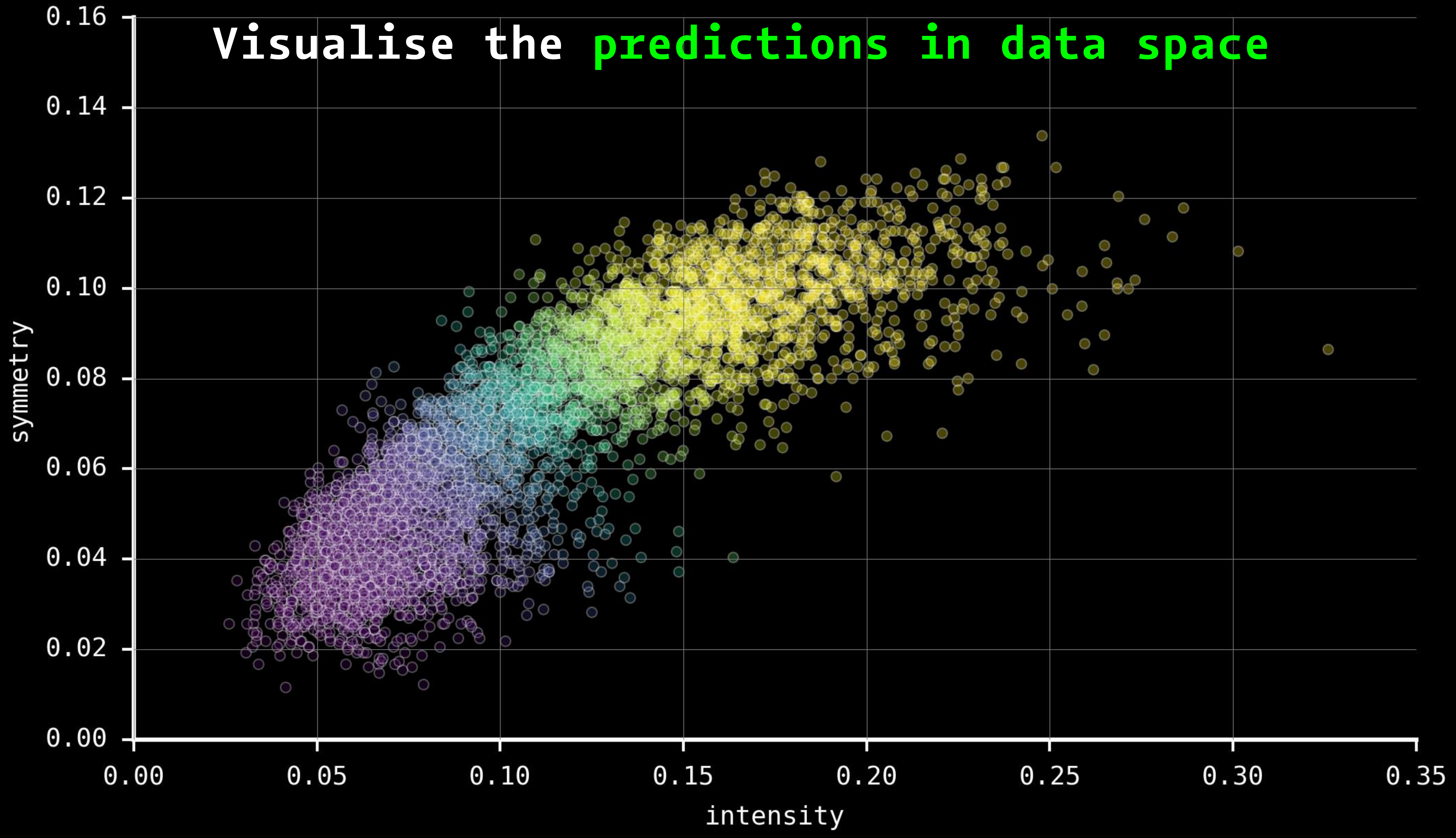


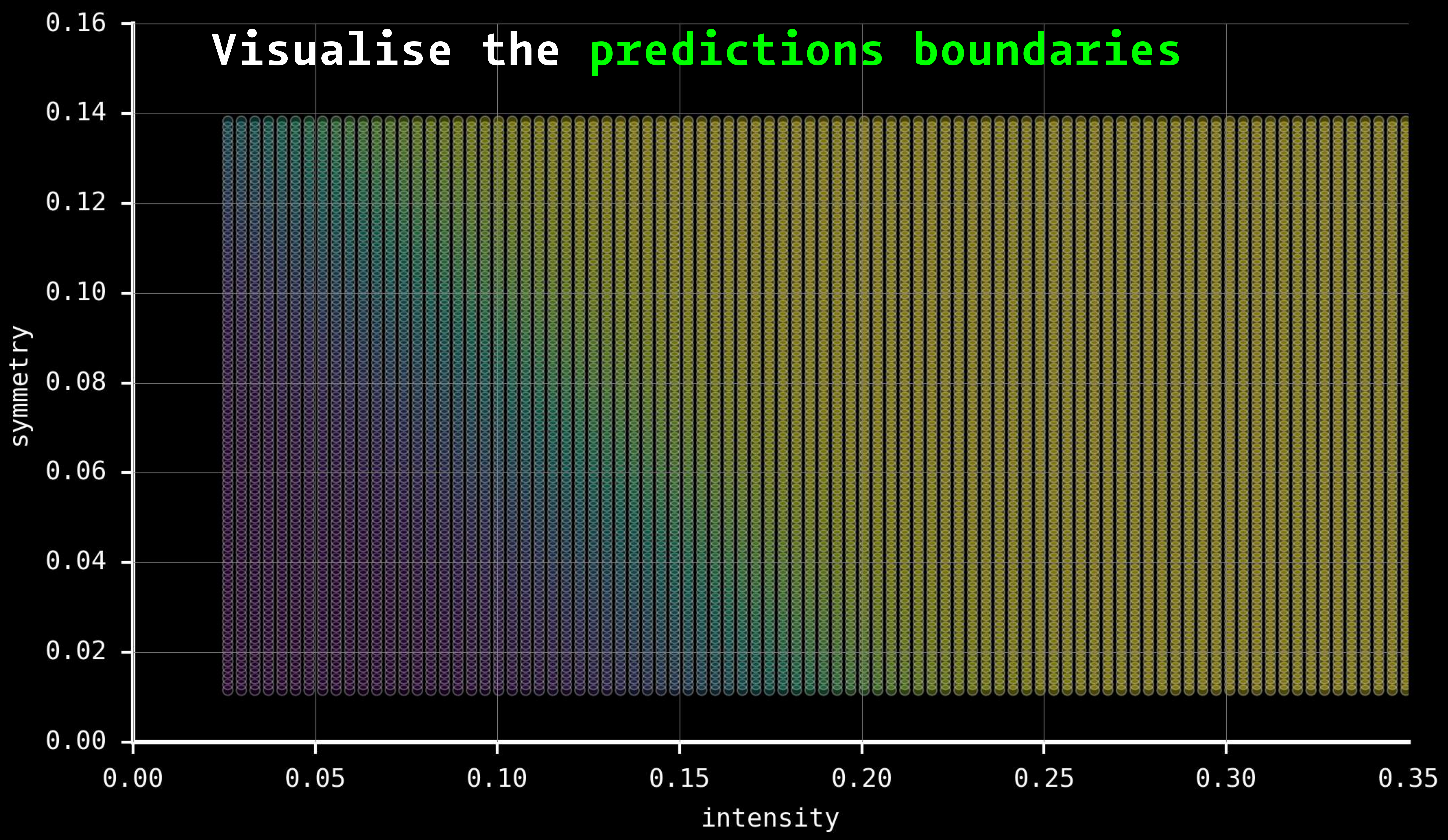




Visualise the reduced feature space
symmetry
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
intensity

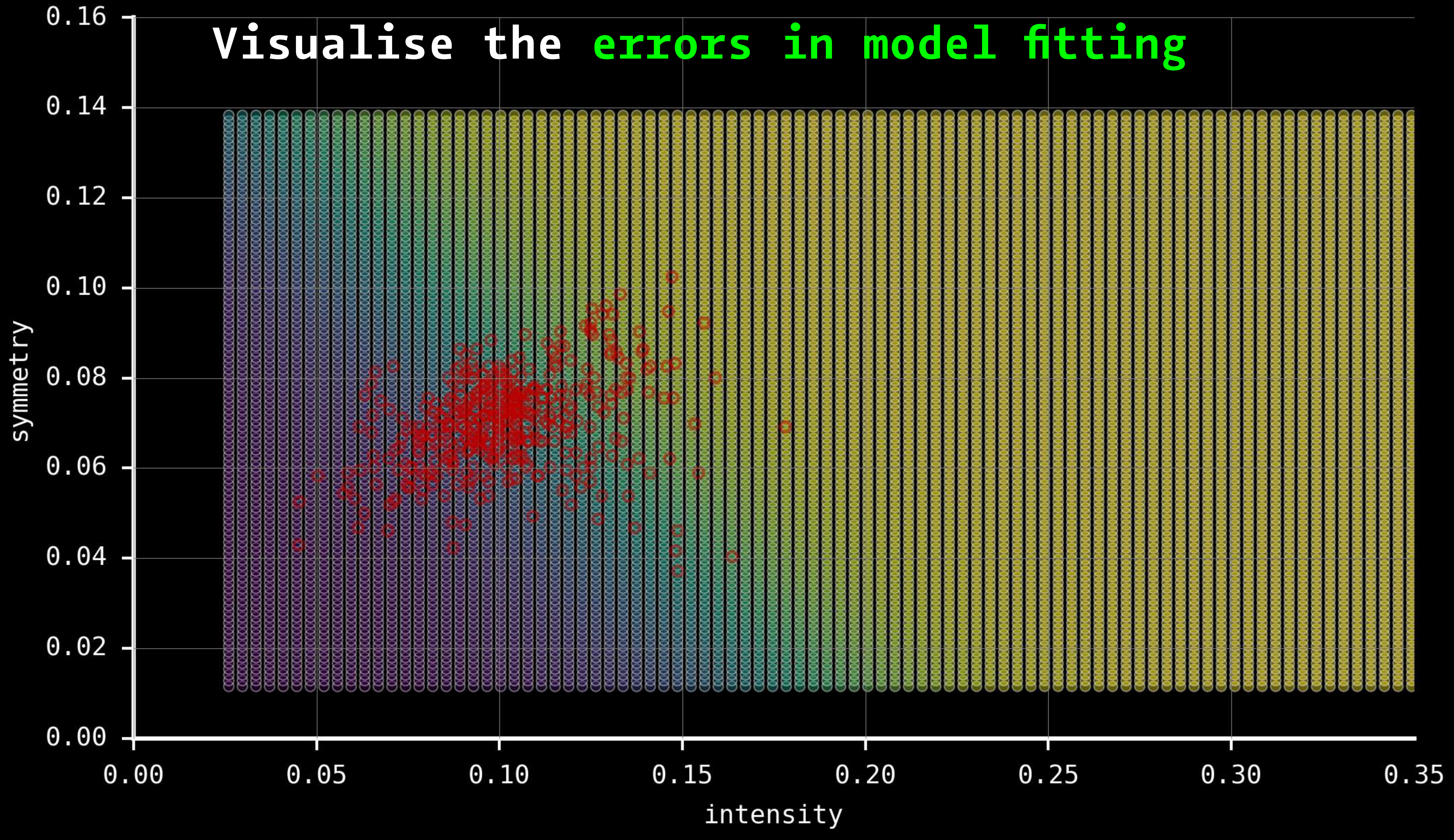
Visualise the predictions in data space



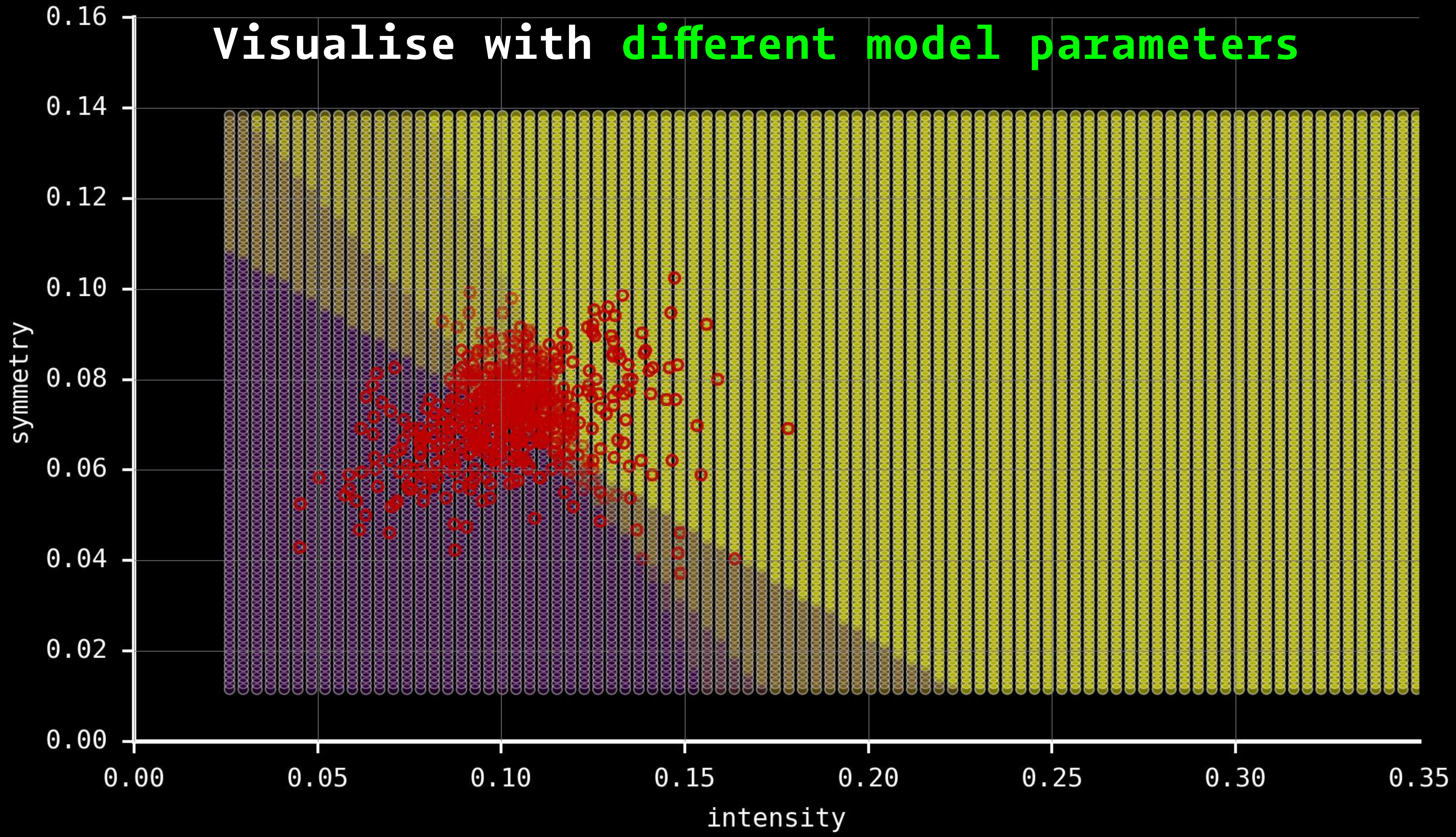


Visualise the predictions boundaries
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
symmetry
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
intensity

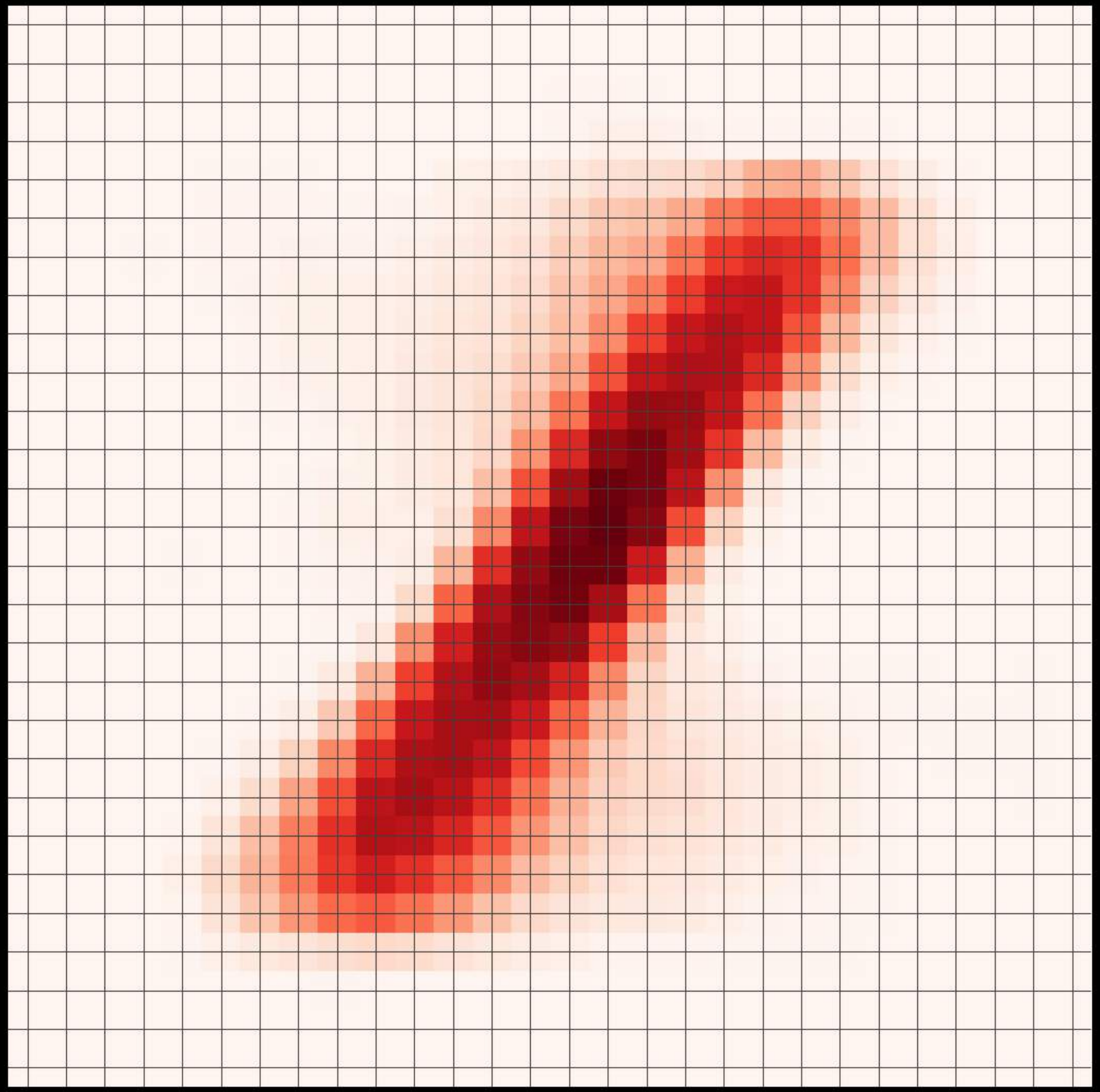
Visualise the errors in model fitting

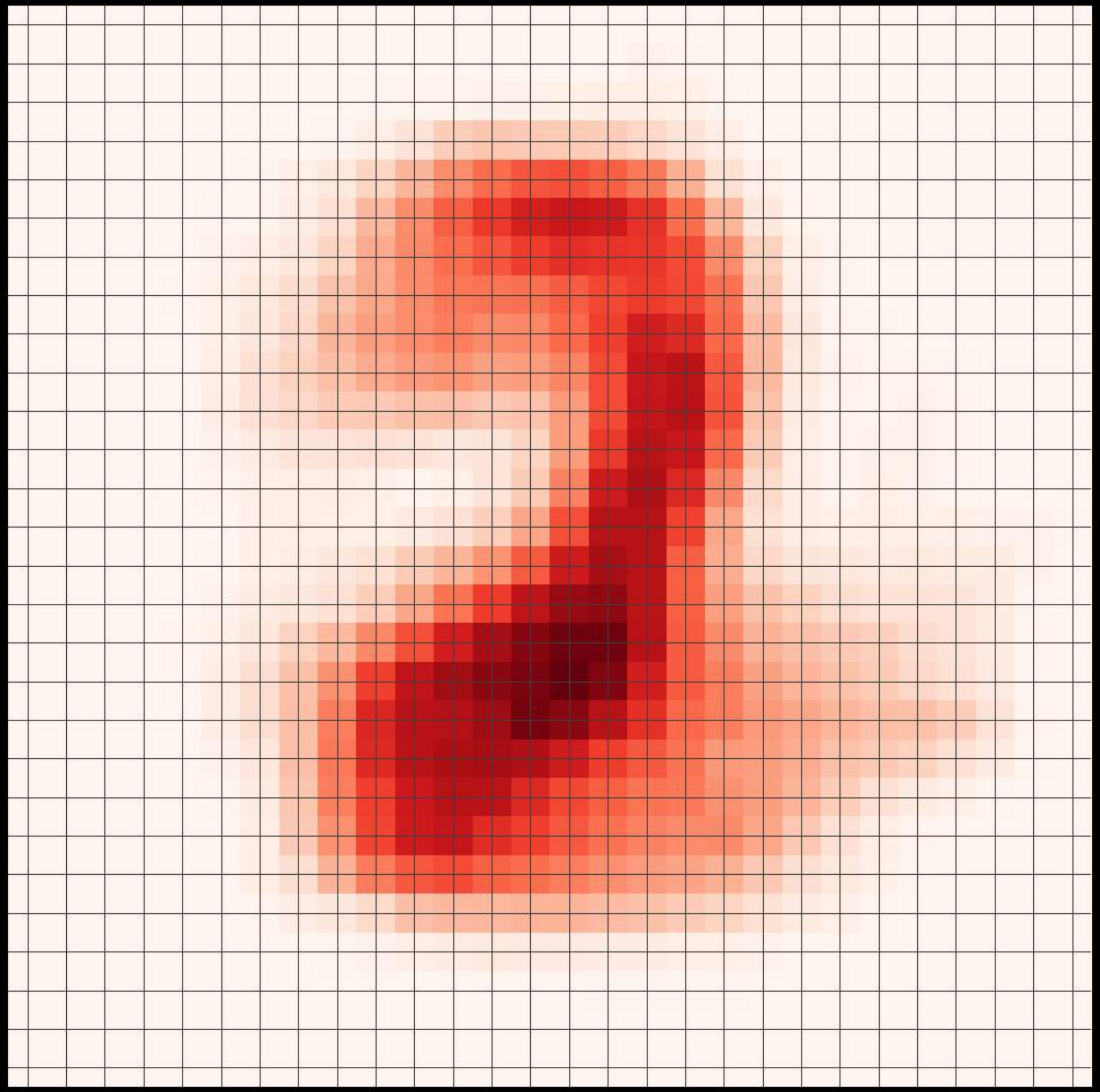


Visualise with different model parameters



Easy to visualise errors in data space



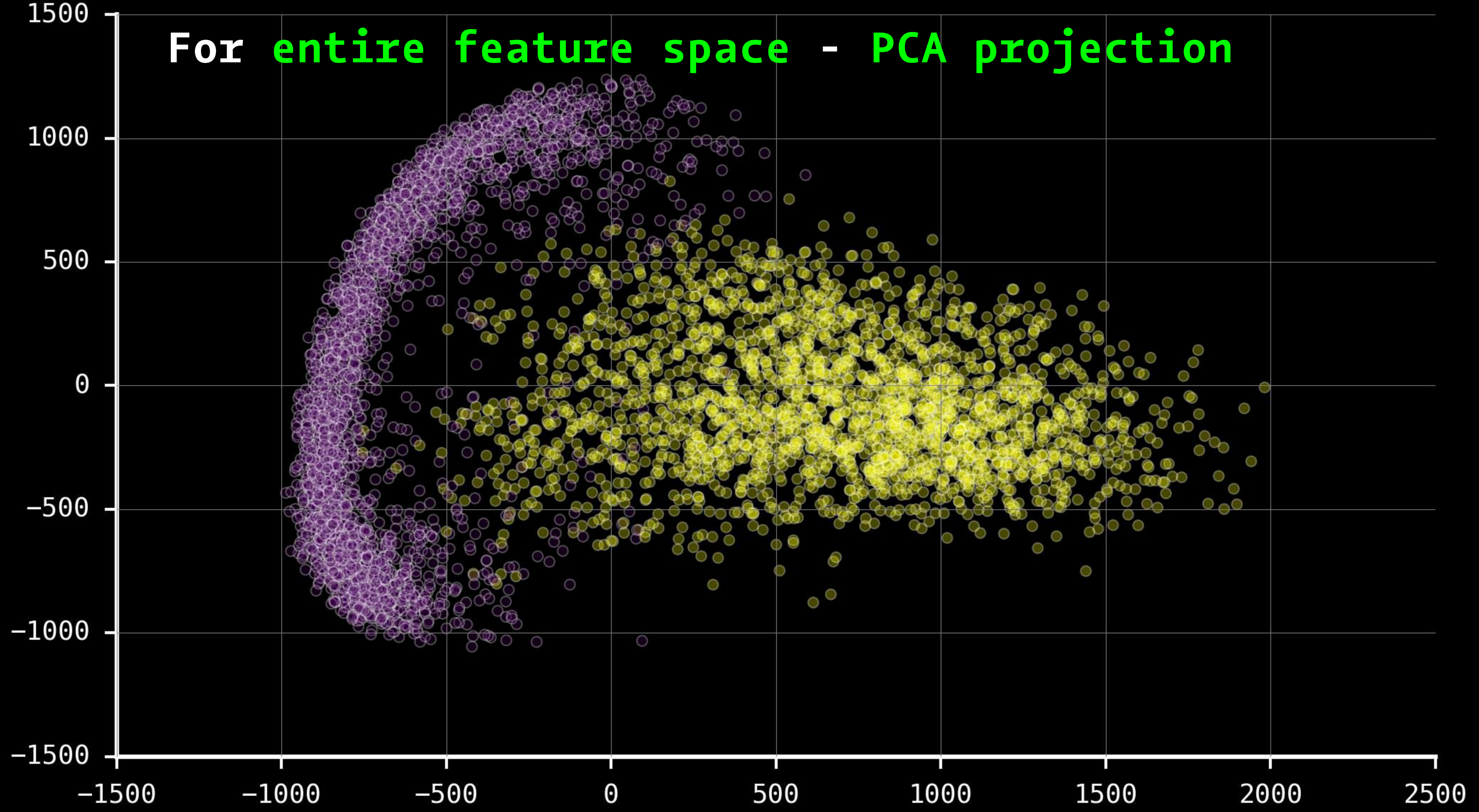


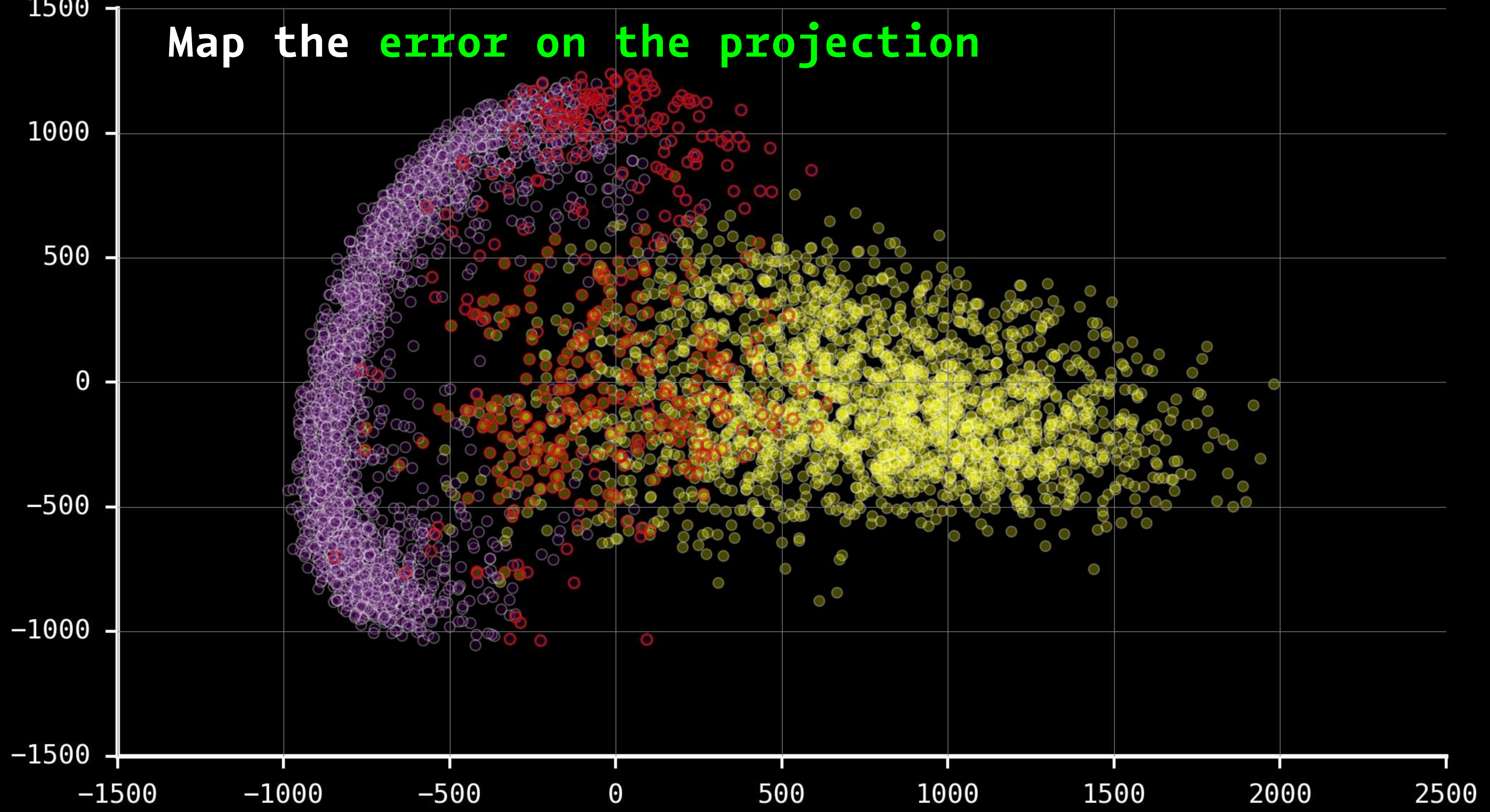
How to scale for large p?

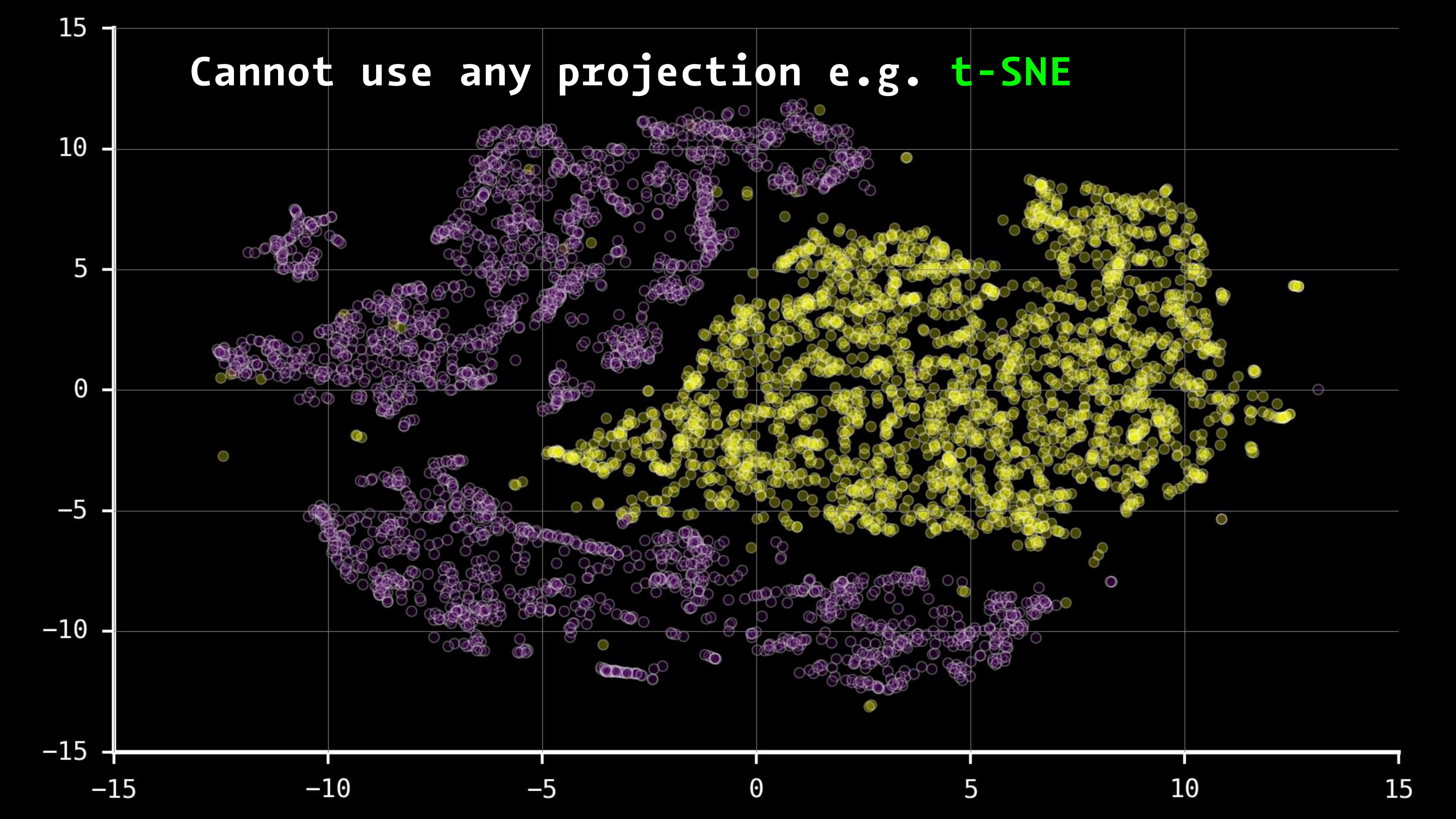
Curse of dimensionality

Mesh approach computationally expensive

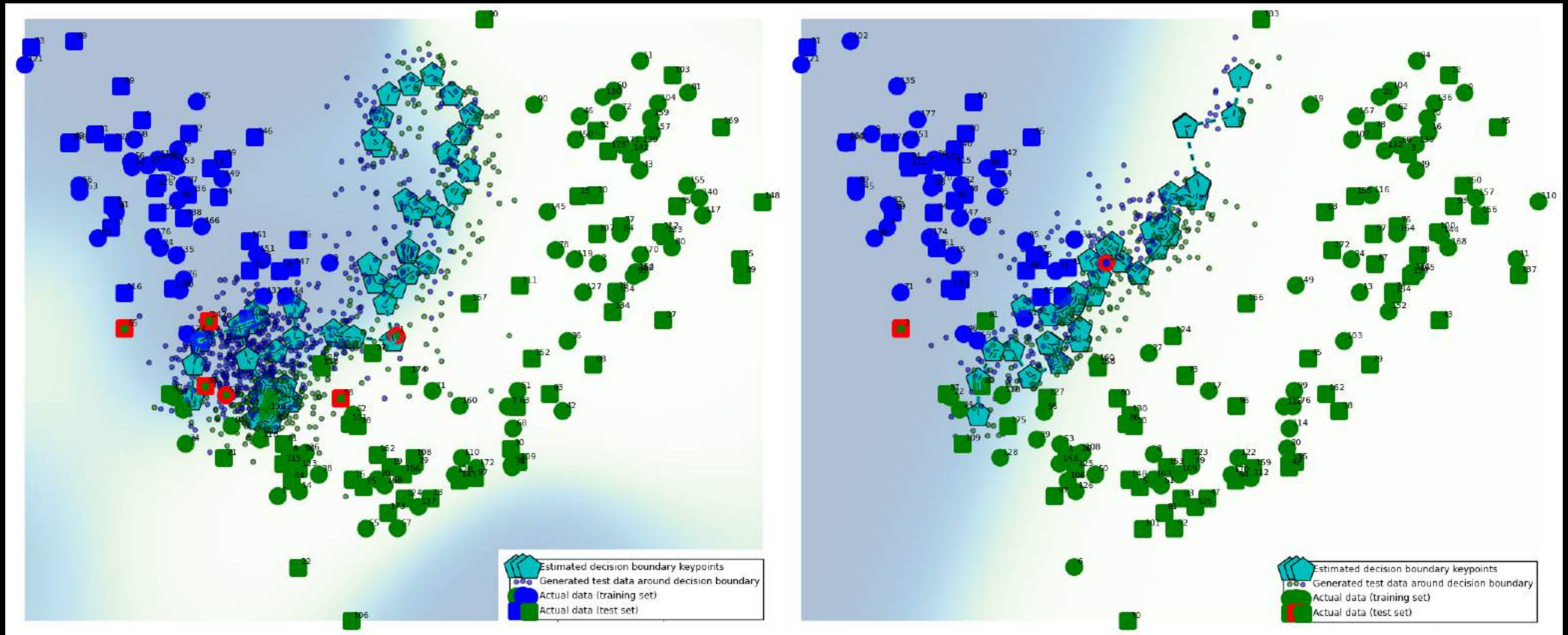
Need to use projections


For entire feature space - PCA projection
1500
1000
500
0
−500
−1000
−1500
−1500
−1000
−500
0
500
1000
1500
2000
2500


Map the error on the projection
1500
1000
500
0
−500
−1000
−1500
−1500
−1000
−500
0
500
1000
1500
2000
2500


Cannot use any projection e.g. t-SNE
15
10
5
0
−5
−10
−15
−15
−10
−5
0
5
10
15

High-p Boundary Classifiers



Github: highdimensional-decision-boundary-plot

Regression: Large n

NYC Taxi Trip Data

n ~ 10M (in just one month)

p = 20, geo location (drop & pick up), fare breakup, passenger no. etc.

Data-Vis Issue

Plotting is hard e.g. alpha

Sampling (~1%) may be effective

Require careful tuning parameters e.g. overweighting unusual values

Binning Helps

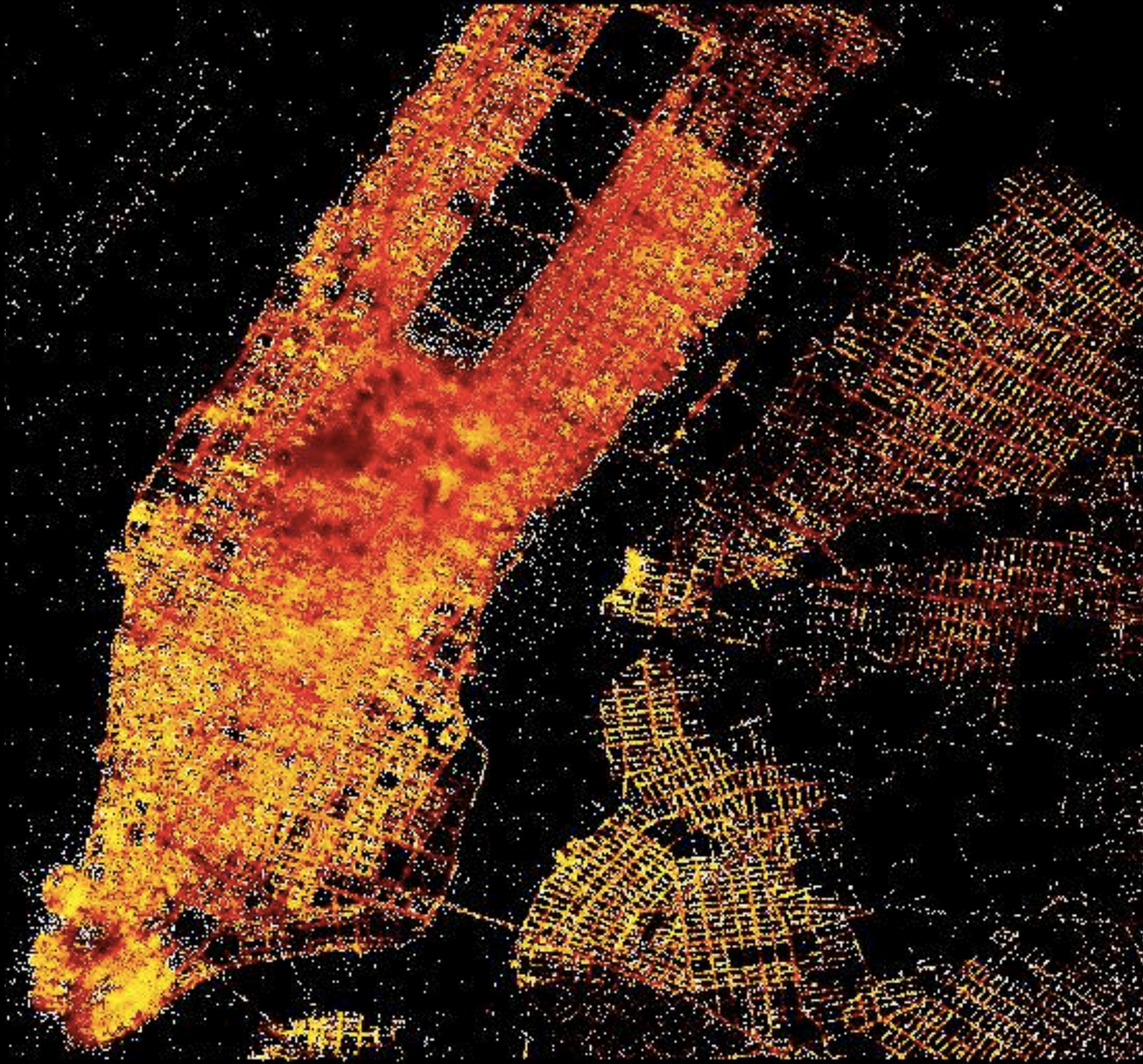
“Bin - Summarize - Smooth: A framework for visualising big data” - Hadley Wickam
Package in R: 'BigVis' (2013)

Recent Interactive implementation in Python
Package in Python: 'Datashader' (2016)

Vis Data Space

Plot the **probability of getting a tip**

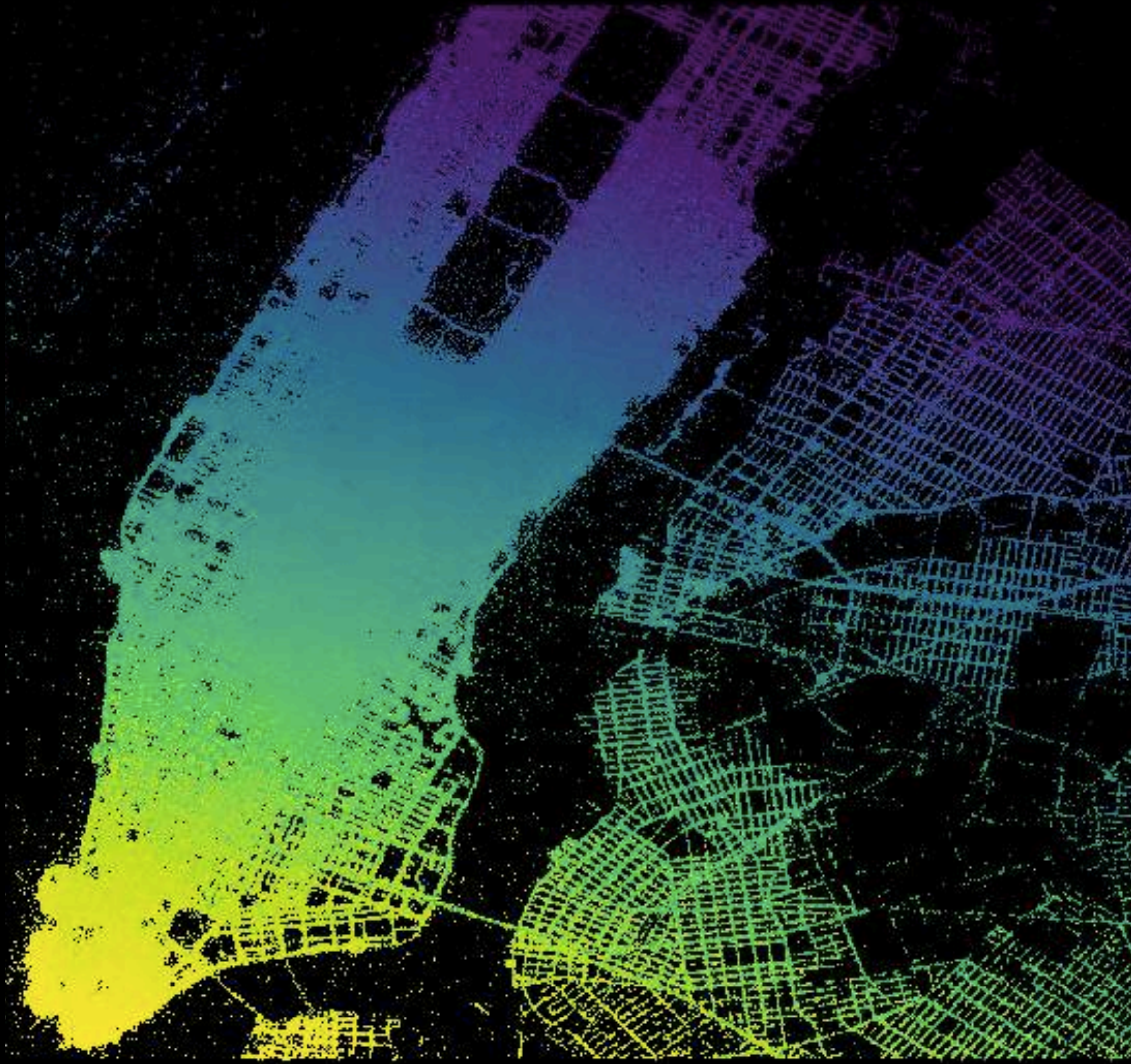
Start to see the patterns in the visualisation



Vis Predictions

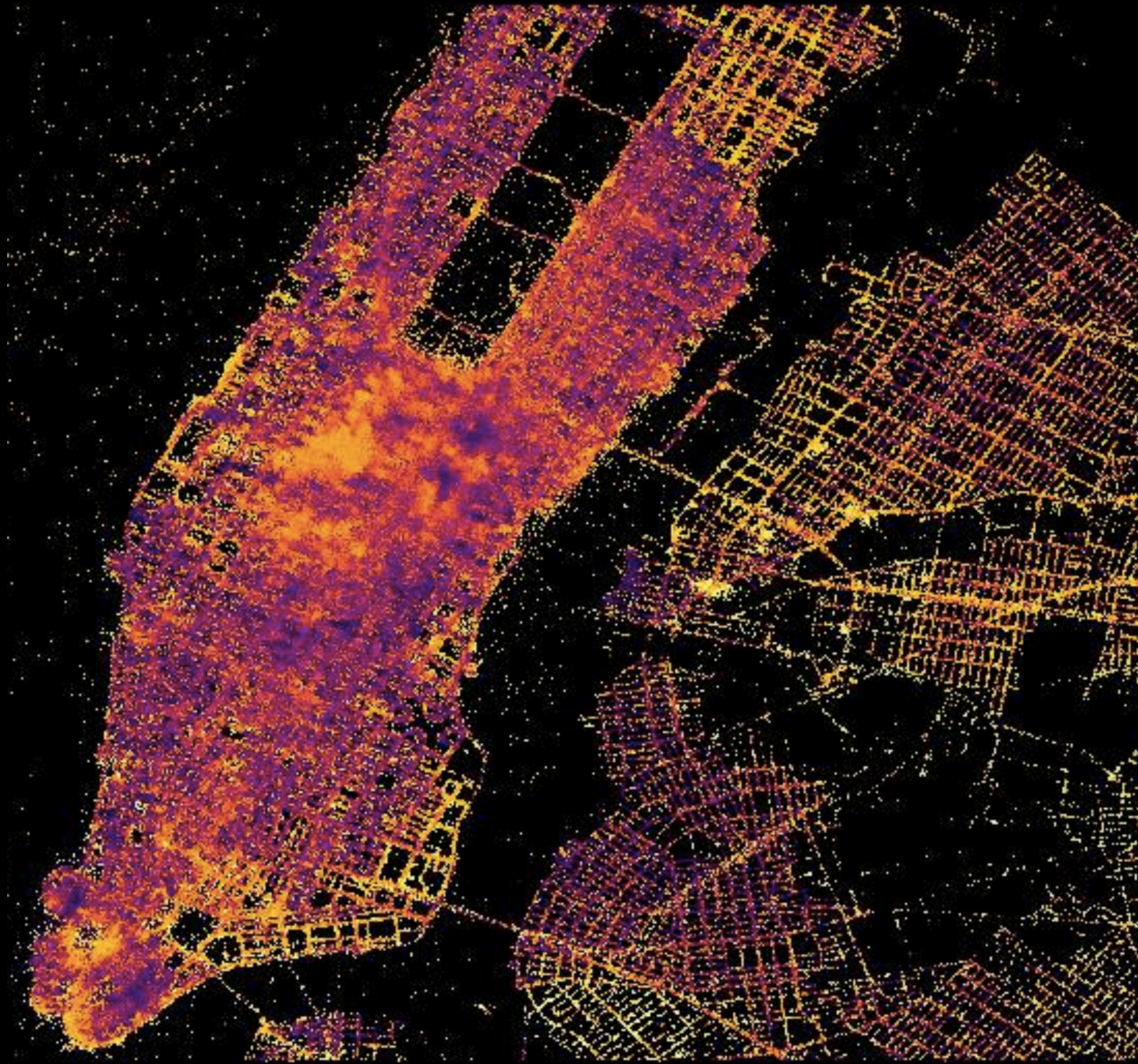
Predict the probability of getting tip

Simple Linear Model - drop coords, passenger count, time and day of week



Vis Errors

Visualise the errors in tip probability distribution



N-Models Challenge

Model Explosion

Entire Model Space

+ Add *Tuning* Models

+ Add *Bootstrap* Models

+ Add *Ensemble* Models

+ Add *Cross-Validation* Models

N-Models Challenge

Keep track of prediction & errors

Keep track of model output parameters

Tidy Model

Augment predictions & errors to dataset

Create output parameters data frame

Visualise like Tidy Data

Managing N-Models

"Managing Many Models in R"

by Hadley Wickham

"Broom Package in R

by David Robinson

p/n/N Model-Vis challenge

---

p -- High dimensional data

n -- Large and big data

N -- Multiple models

p/n/N Model-Vis approach

---

p -- use Projections

n -- use Binning or Sampling

N -- use Tidy Model

Model-Vis

Similar challenges to Data-Vis

More an Art, than a Science

Essential in ML Model Pipeline

Both to Explain or to Predict

Scope for easier tooling

Model-Vis

Slides and Code

http://modelvis.amitkaps.com

Mini-Site and Explanation (by End of 2016)

Model Visualisation

Amit Kapoor
@amitkaps

amitkaps.com