Time Series Forecasting: Population levels in Austin Animal Shelter

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Contents

Problem and solution

Problem: For resourcing and budgeting reasons, animal shelters need to accurately forecast the animal population.

Solution:

- Build a time series model to forecast the population ahead 1 year
  - Ensure it can be re-run with updated data as required
- Aim to make the model as accurate as possible

Data – Overview

data.austintexas.gov

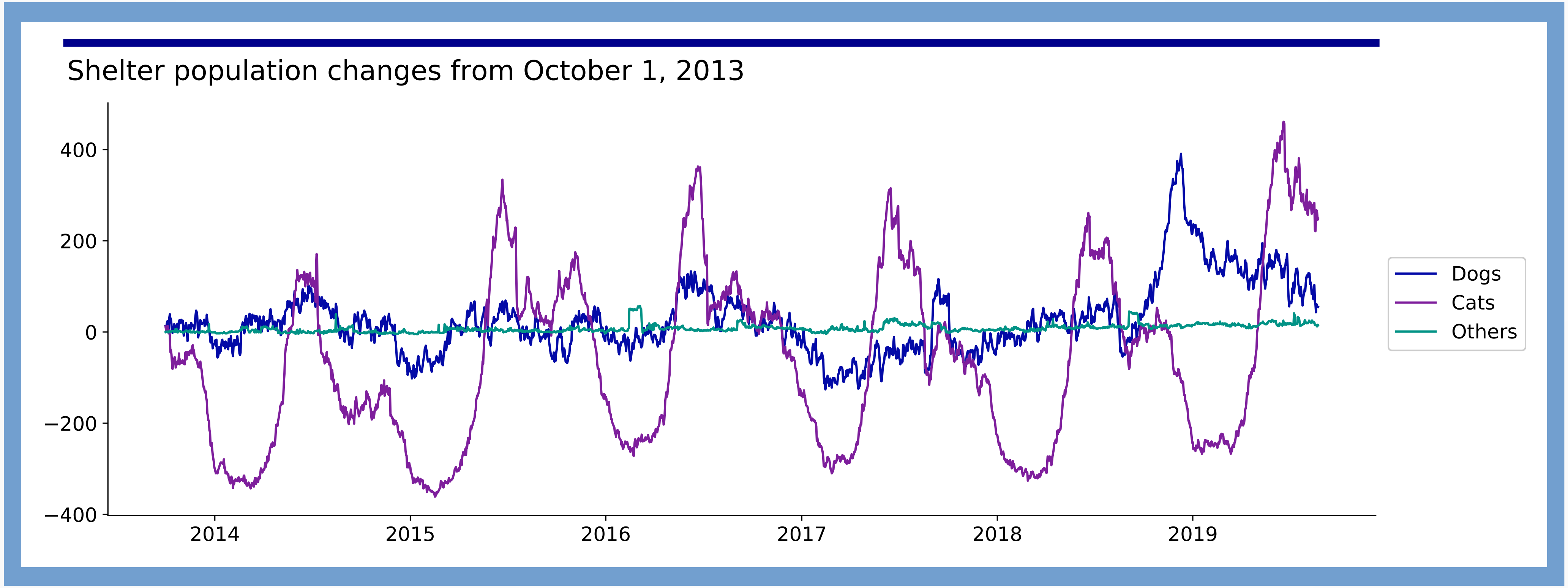
October 1, 2013 to present day

5 animal categories: dogs, cats, birds, livestock and other

Data preprocessing required:

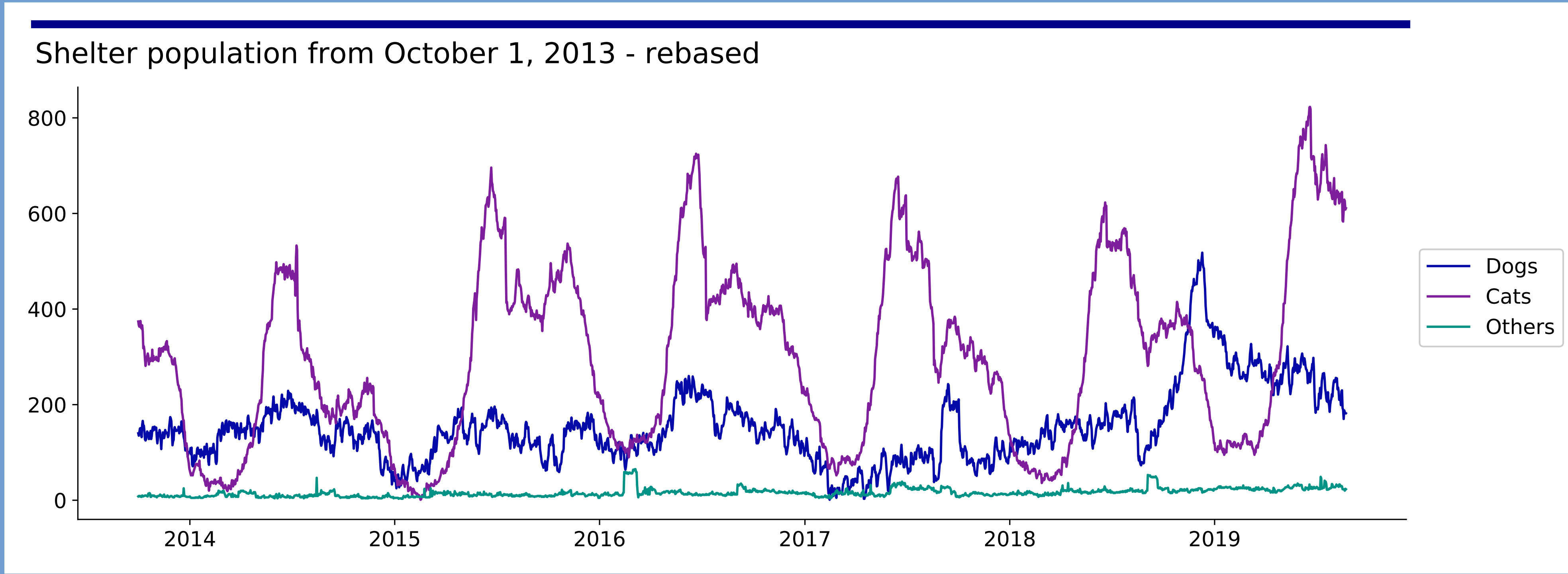
- Convert intake/outtake to population
- Group birds, livestock and other into single category
- Create time series variables where required

Data – Animal population



- Annual seasonality for cats
  - Maybe for dogs too
  - Potential weekly seasonality but hard to see
- Divide by zero errors could be an issue

Data – Animal population



- Rebased population data so never goes to zero
- Potential increasing trend visible?

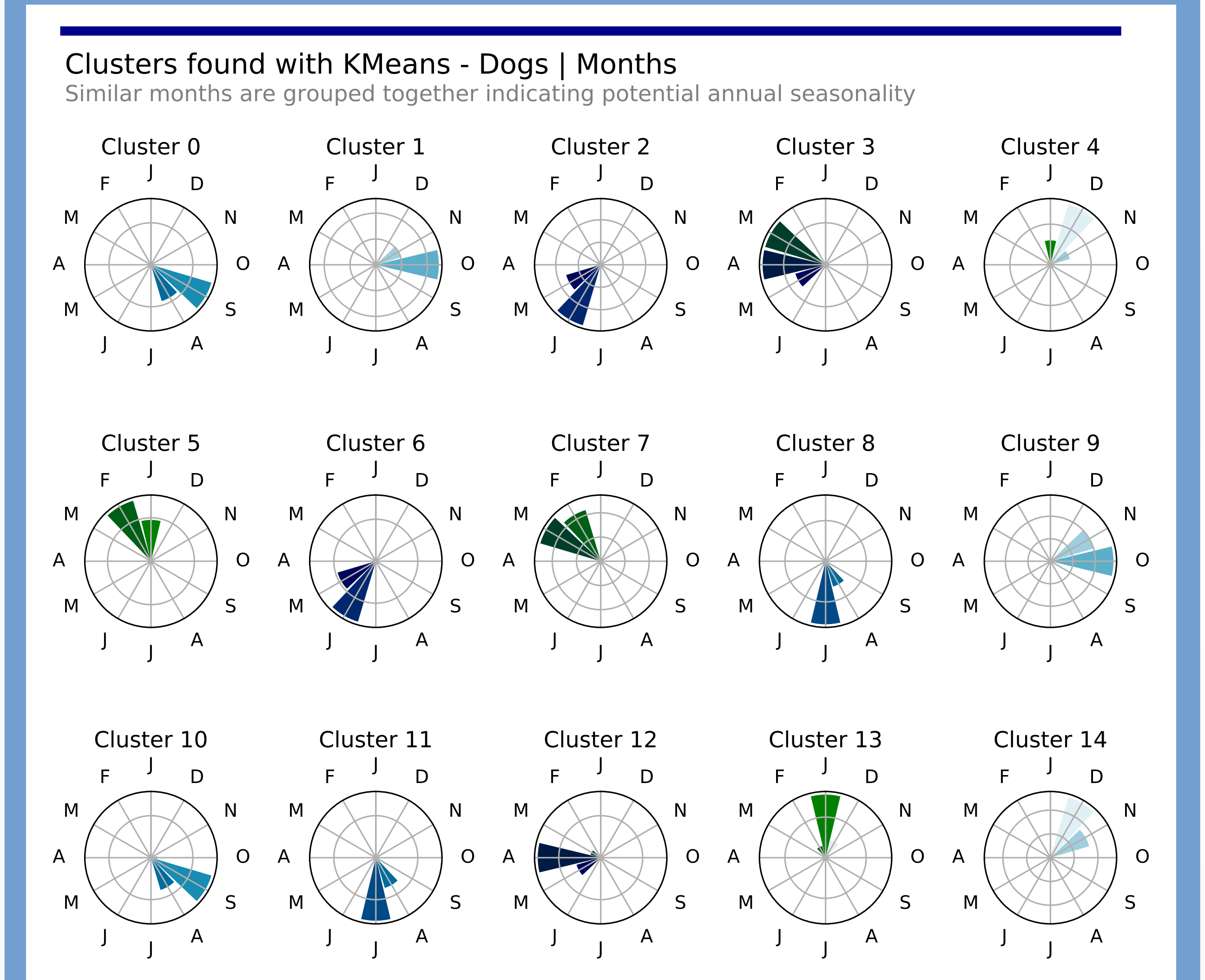
Unsupervised learning - Seasonality

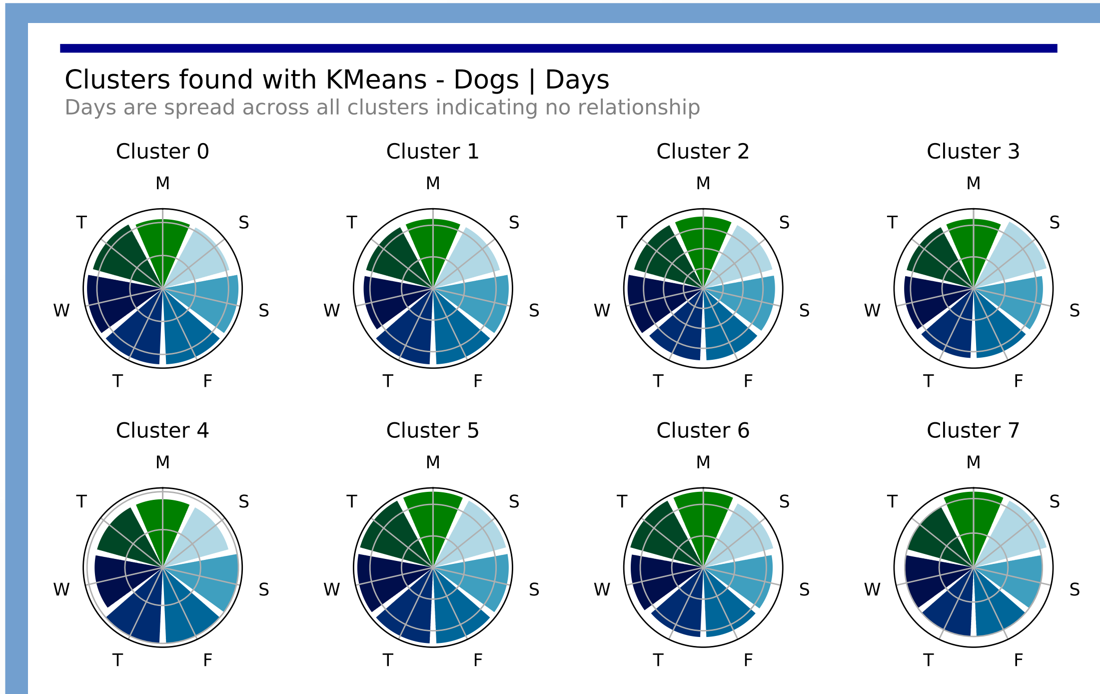
Aim: Use unsupervised clustering techniques to understand what seasonality exists within the data.

How:

- Use a KMeans algorithm
  - Flexible (can try different numbers of clusters)
  - Fast
- Look to see if months / days group together indicating similarity

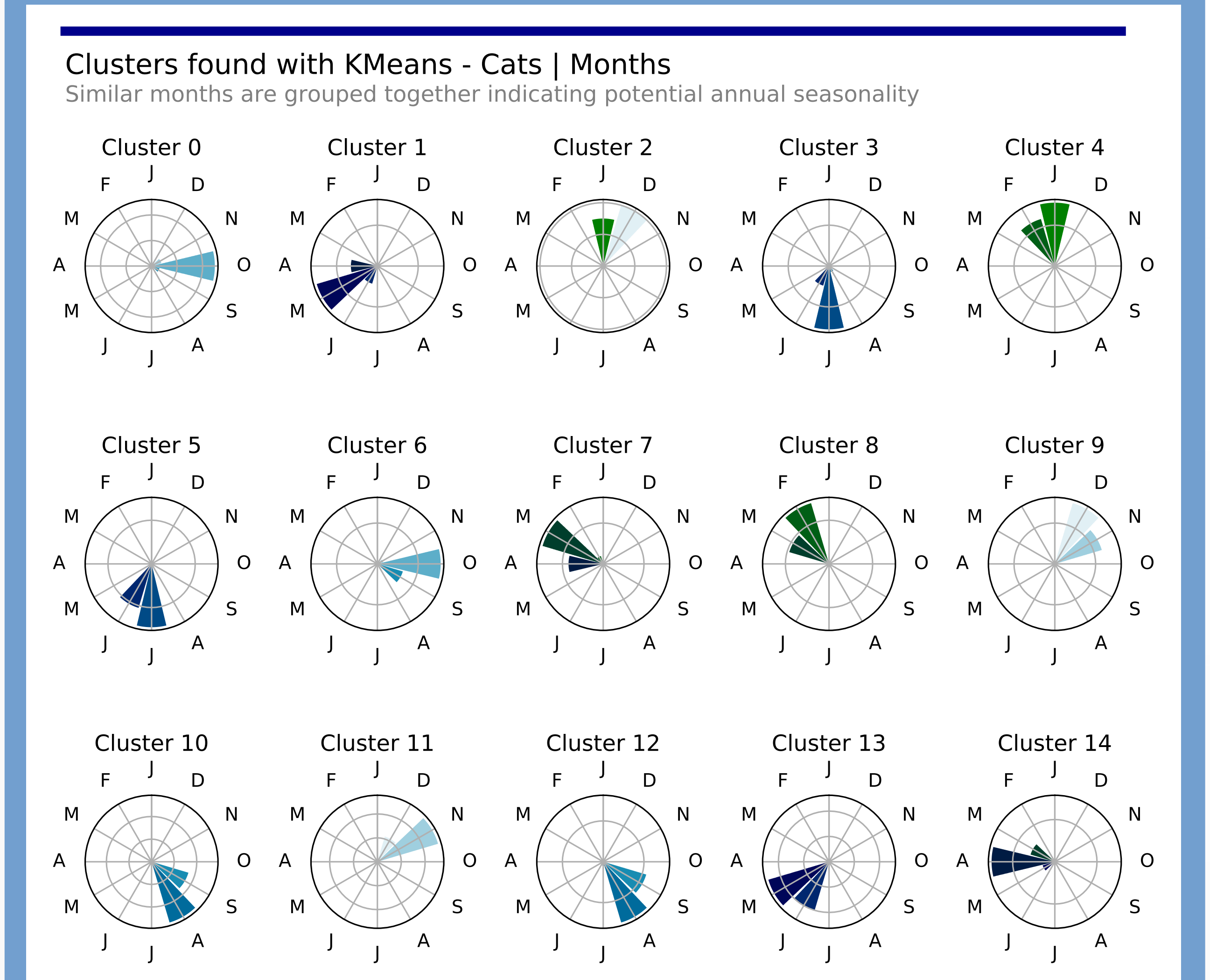
Unsupervised learning - Dogs

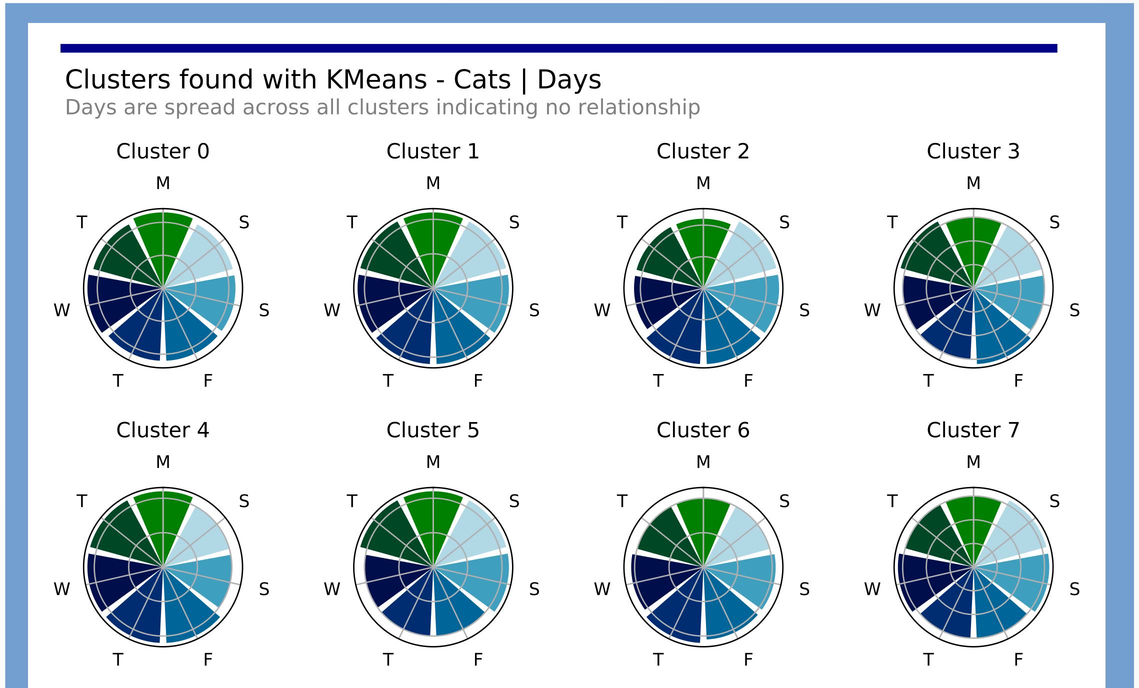




- No visible grouping by day
- Clear grouping by month
  - Not exact month but same time of year

Unsupervised learning - Cats





- No visible grouping by day
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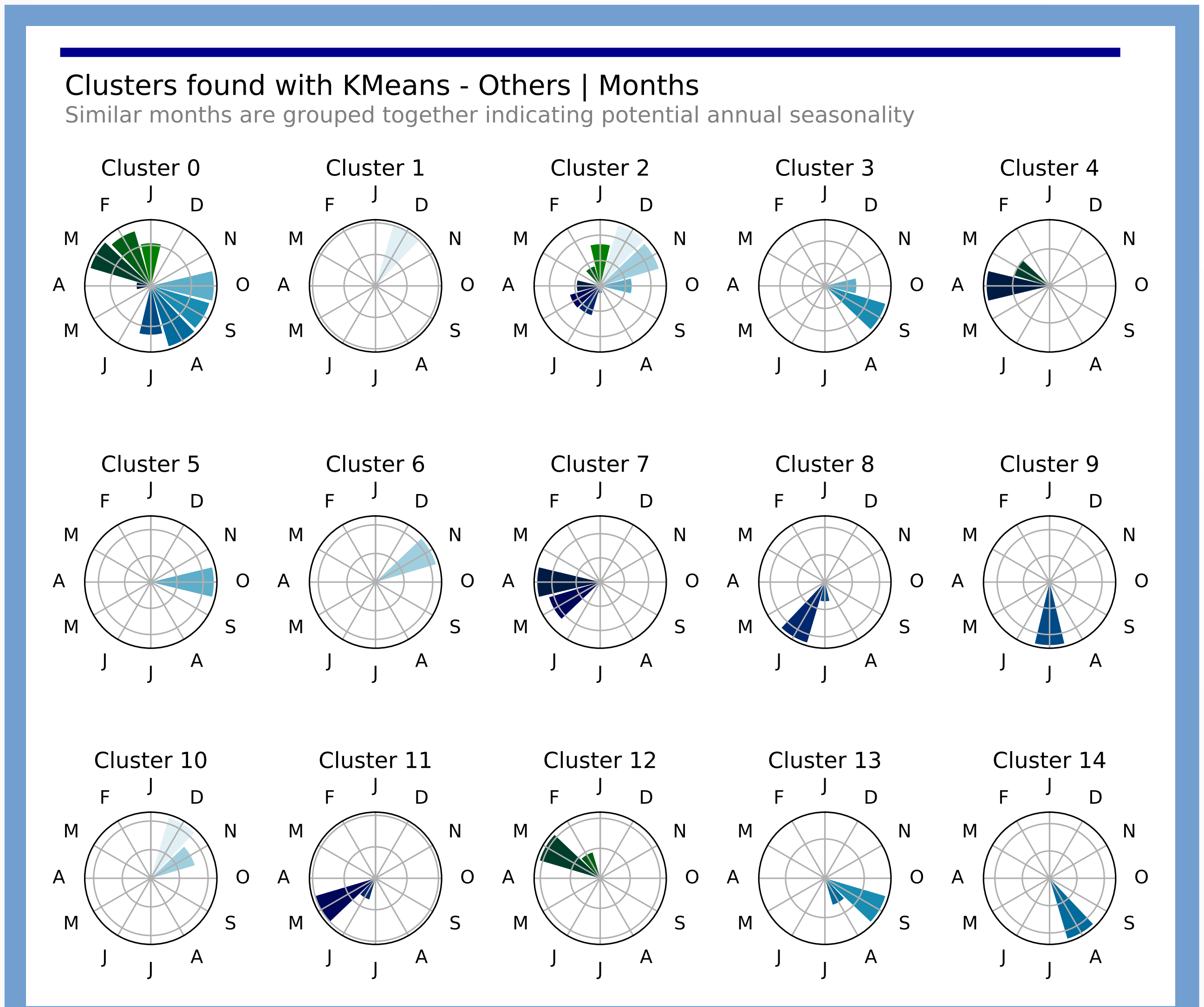
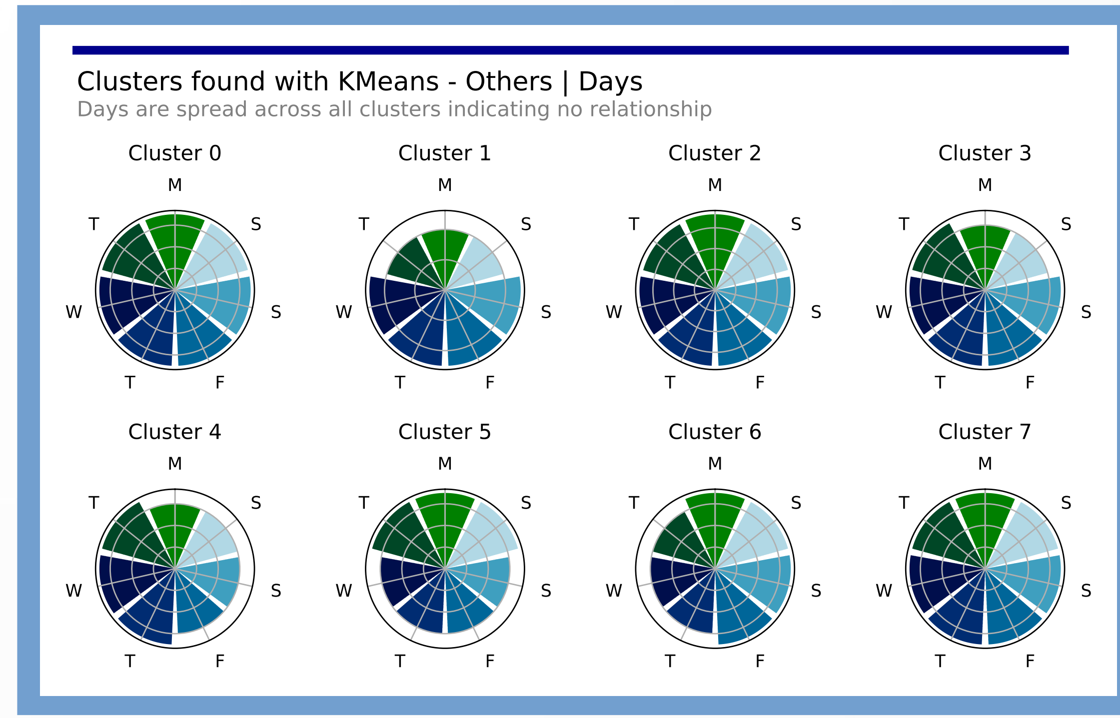
Unsupervised learning - Others





- No visible grouping by day
- Limited grouping by month
  - Concentrated in cluster 0 and cluster 2

Modeling – Algorithms tested

Baseline algorithms

Naive

Assumes future values will be equal to the most recent known value.

Seasonal Naive

Assumes future values will be equal to the average of the known values at the same date.

Time series algorithms

ARIMA

Assumes future values are based on previous terms and previous errors.

Prophet

Algorithm developed by Facebook which separately models trend and seasonality.

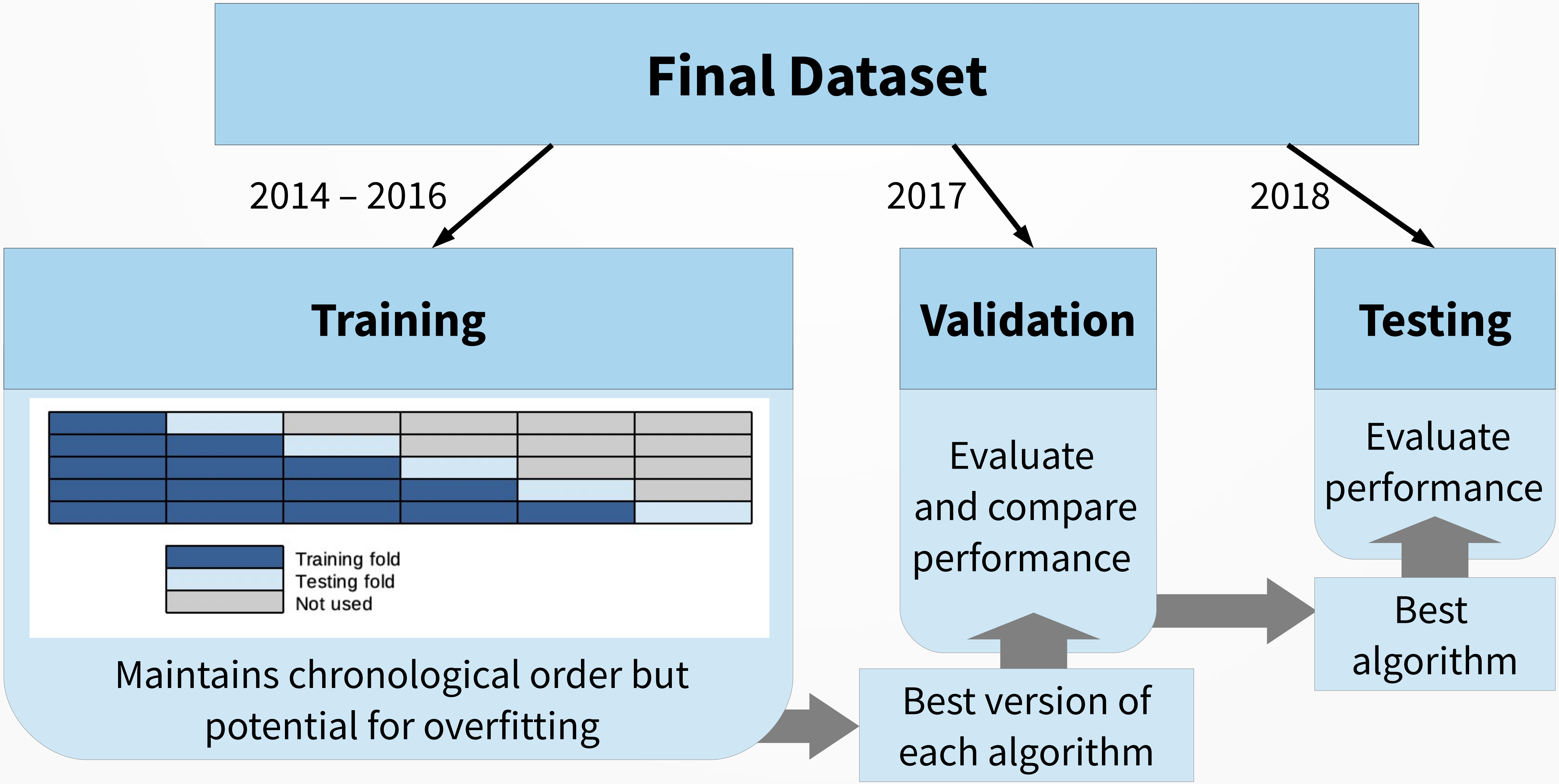
Neural Network

Supervised learning technique which uses previous terms as features to learn from.

Random Forest

Supervised learning technique which uses previous terms as features to learn from.

Modeling – Selection pathway



Modeling – Error evaluation

MAE

$mean(|e_t|)$

- Mean Absolute Error
- Same scale as data
  - Cannot use to make comparisons between different time series
- Minimizing this leads to forecasts of the median

MAPE

$mean(|p_t|)$

$p_t = 100 e_t / y_t$

- Mean Absolute Percentage Error
- Unit free so can compare between different time series
- Gives extreme values when y_t is close to zero and is undefined if y_t is equal to zero

RMSE

$\sqrt{mean(e_t^2)}$

- Root Mean Squared Error
- Same scale as data
  - Cannot use to make comparisons between different time series
- Minimizing this leads to forecasts of the mean

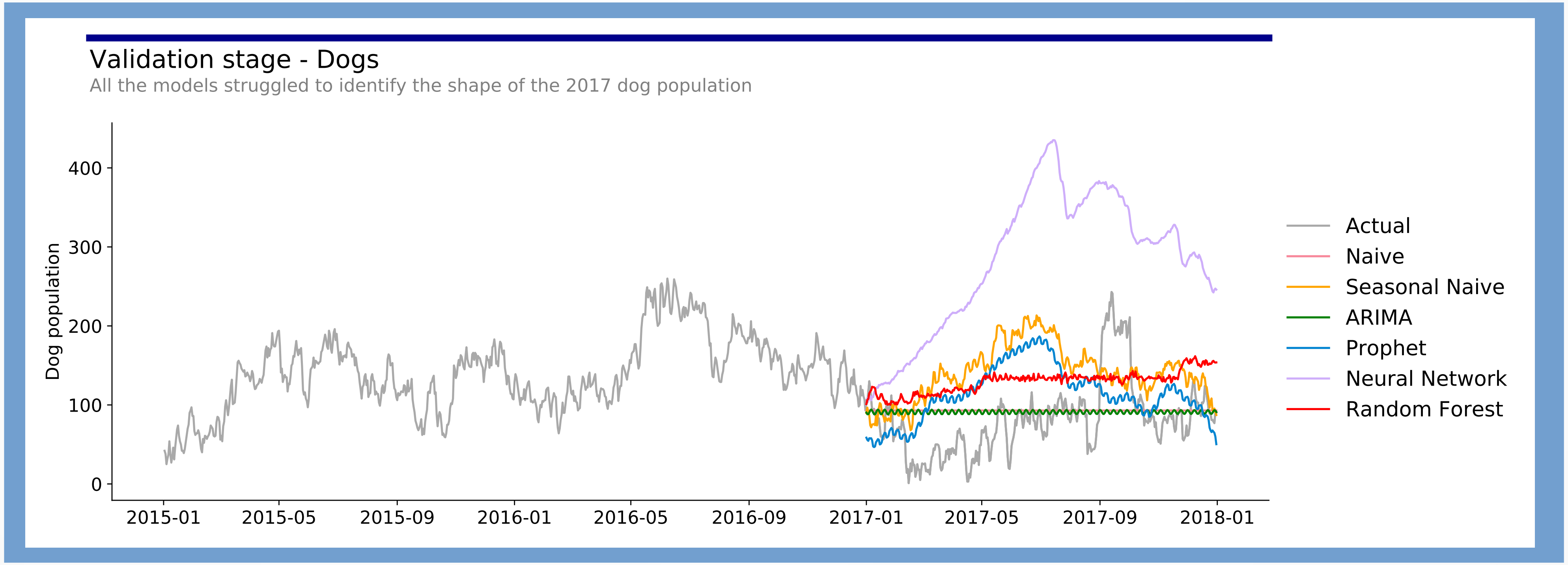
MASE

$mean(|q_j|)$

$$q_j = \frac{e_j}{\frac{1}{T-1}\sum_{t=2}^{T}|y_t - y_{t-1}|}$$

- Mean Absolute Scaled Error
- Can compare between different time series
- Uses a scaled error based on a naive forecast of the training data

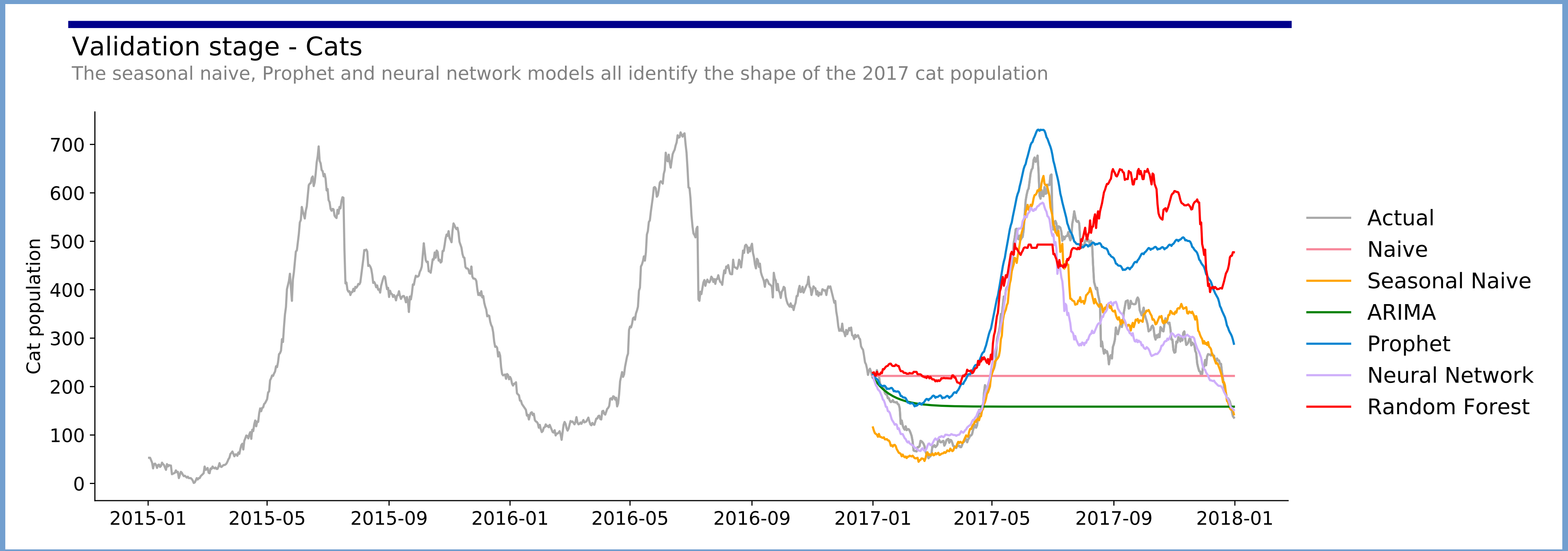
Modeling – Dog validation results



Baselines	MAE	RMSE	MAPE	MASE
Naive	35.5	48.2	125.9	4.2
Seasonal Naive	72.8	82.1	205.1	8.6

TS Models	MAE	RMSE	MAPE	MASE
ARIMA	34.7	47.8	121.2	4.1
Prophet	56.8	66.1	149.4	6.7
Neural Network	201.0	215.9	439.9	23.8
Random Forest	59.6	64.6	181.9	7.1

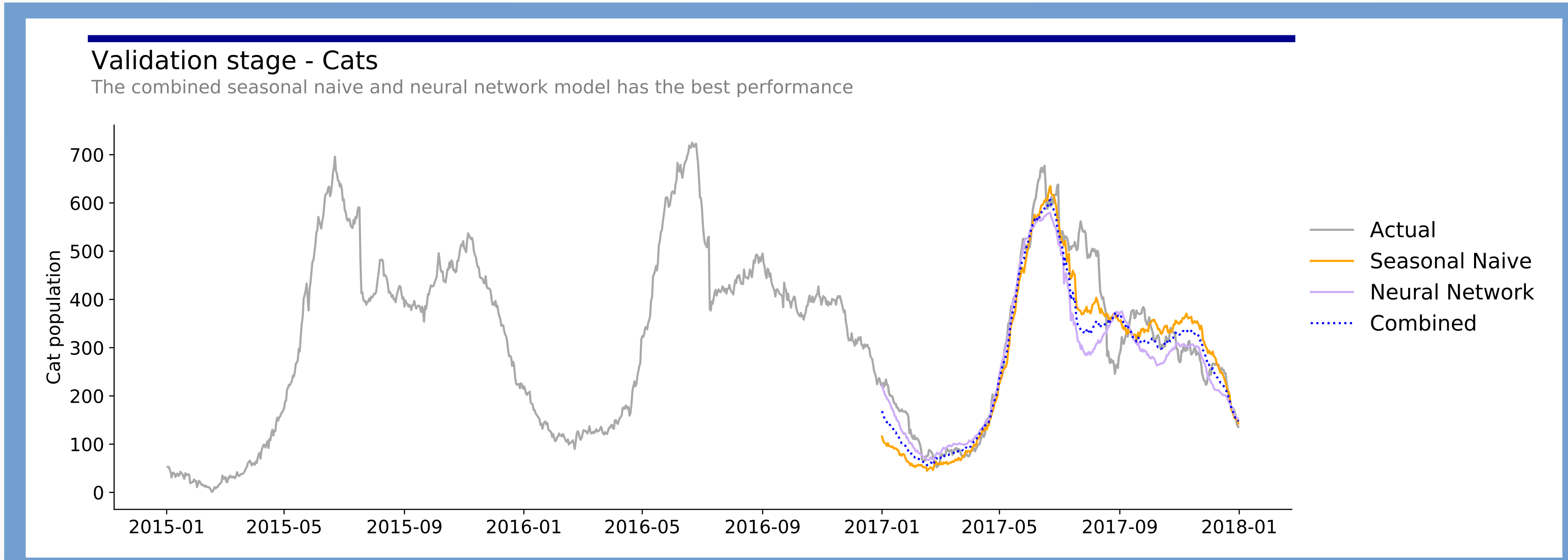
Modeling – Cat validation results



Baselines	MAE	RMSE	MAPE	MASE
Naive	145.7	183.6	63.2	16.9
Seasonal Naive	44.3	58.9	17.9	5.1

TS Models	MAE	RMSE	MAPE	MASE
ARIMA	170.2	217.8	57.0	19.7
Prophet	108.2	123.0	55.3	12.5
Neural Network	47.5	71.8	16.0	5.5
Random Forest	158.4	188.8	79.6	18.3

Modeling – Cat validation results 2



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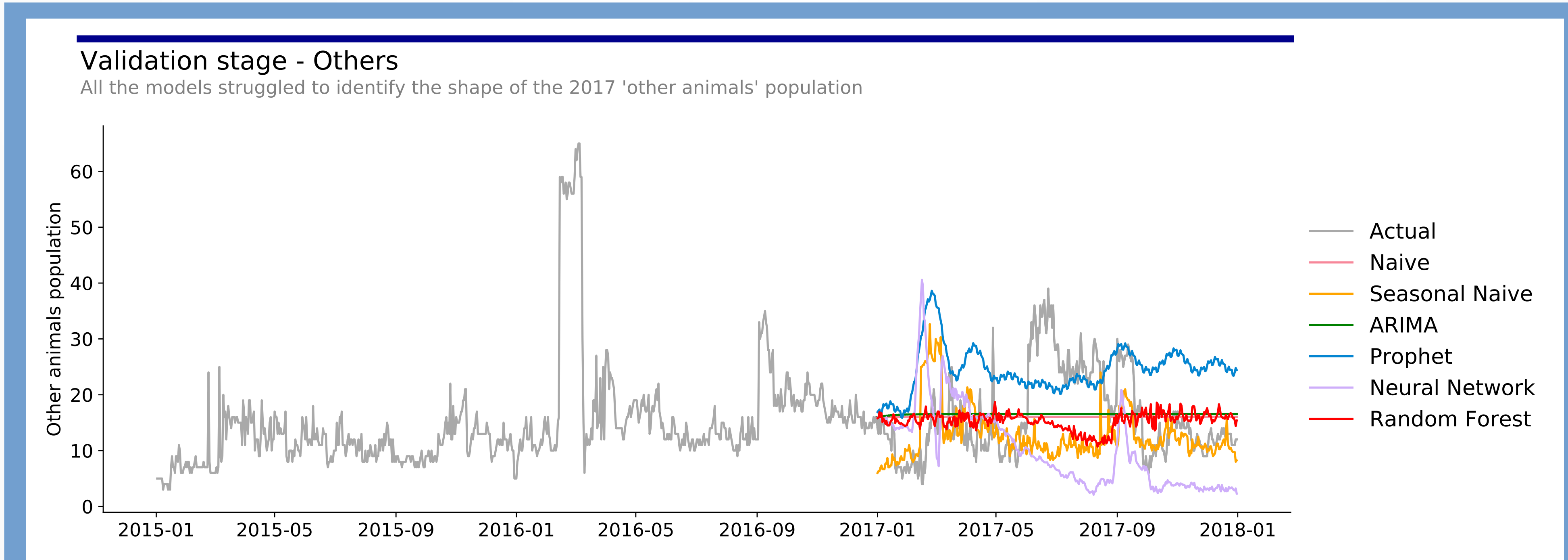
Prophet	108.2	123.0	55.3	12.5
Neural Network	47.5	71.8	16.0	5.5
Random Forest	158.4	188.8	79.6	18.3
Combined	42.5	61.2	15.2	4.9

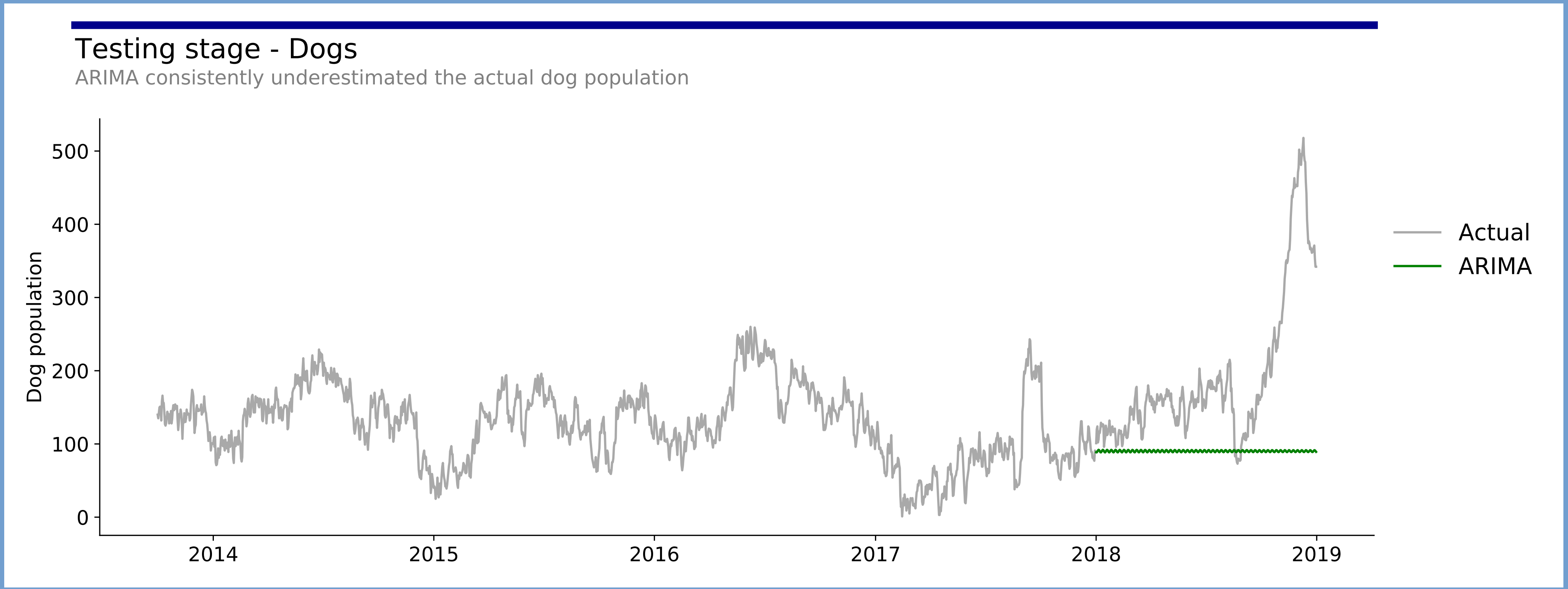
Modeling – Other validation results



Baselines	MAE	RMSE	MAPE	MASE
Naive	6.3	7.7	45.2	3.3
Seasonal Naive	7.1	9.9	42.0	3.8

TS Models	MAE	RMSE	MAPE	MASE
ARIMA	6.4	7.7	47.5	3.4
Prophet	10.7	12.2	93.3	5.7
Neural Network	10.7	13.2	70.6	5.7
Random Forest	6.9	8.5	47.2	3.6

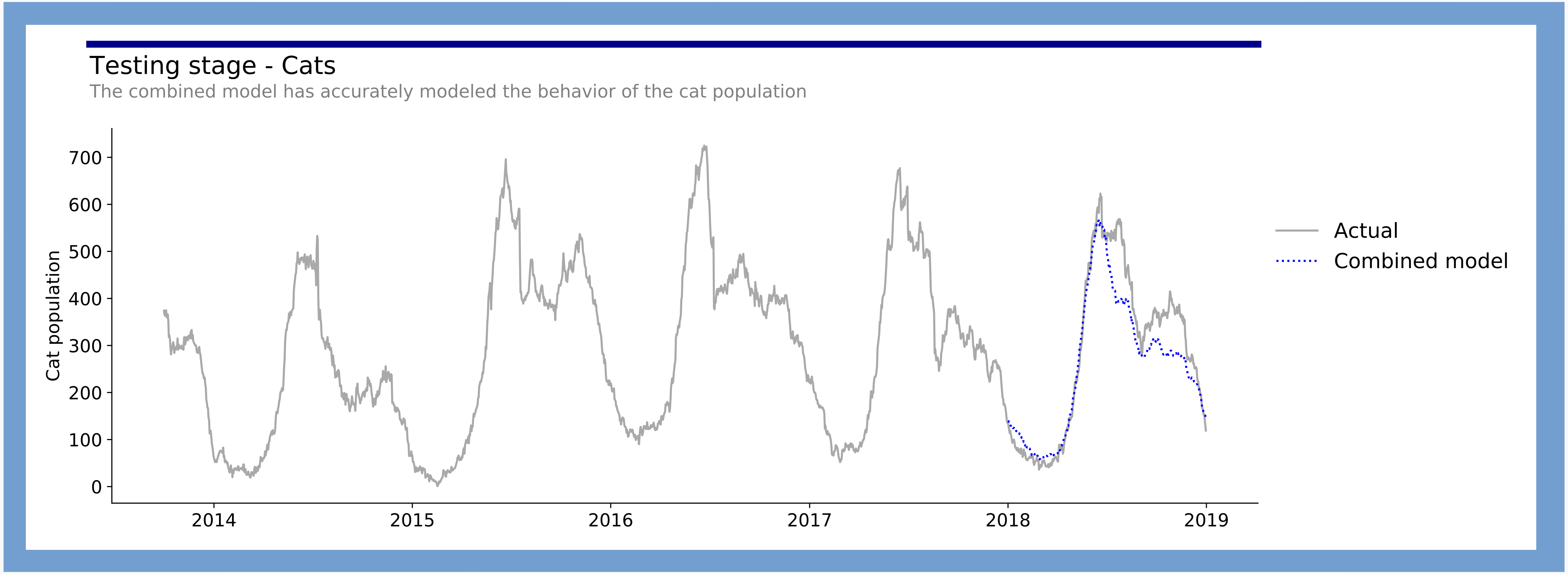
Modeling – Dog test results



	MAE	RMSE	MAPE	MASE
Test	131.1	159.1	52.3	14.9
Validation	*34.7*	*47.8*	*121.2*	*4.1*

- Forecasts almost constant value
  - Misses upward trend
- Spike is unusual – perhaps unpredictable

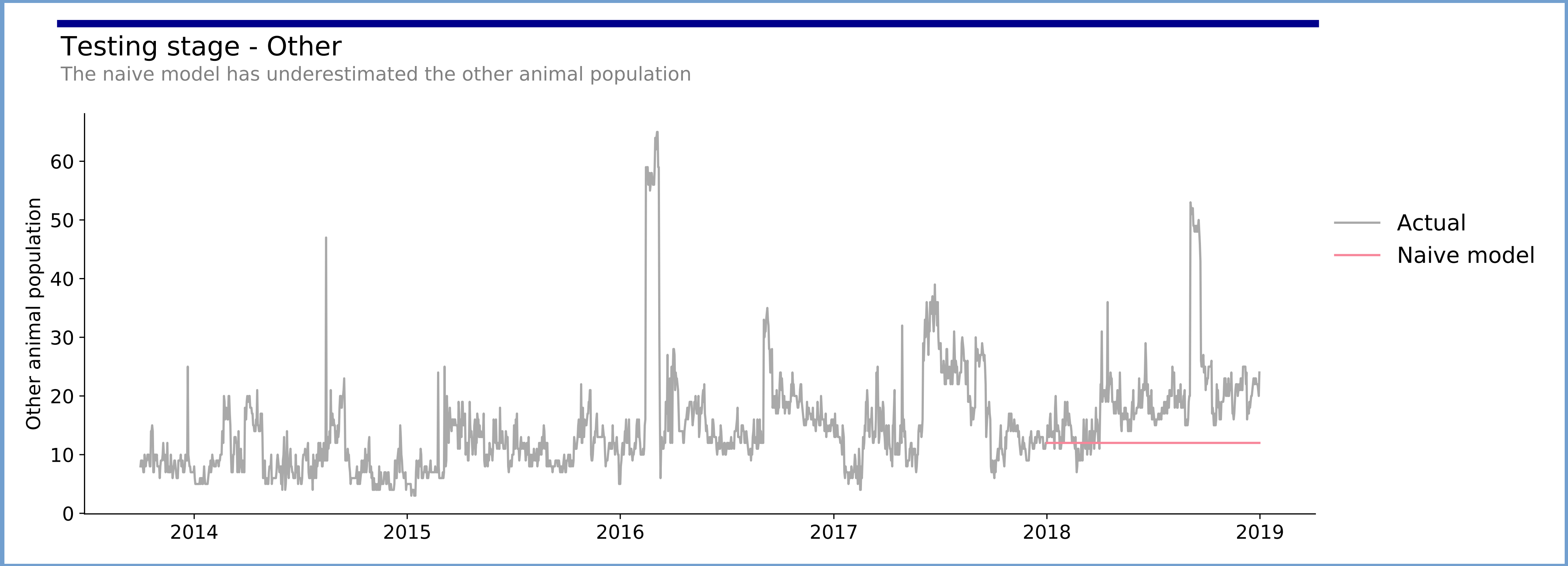
Modeling – Cat test results



	MAE	RMSE	MAPE	MASE
Test	88.0	125.1	27.6	9.8
Validation	*42.5*	*61.2*	*15.2*	*4.9*

- Tracks seasonal pattern very well
  - Misses secondary peak
- Overall slightly underestimates

Modeling – Other test results



	MAE	RMSE	MAPE	MASE
Test	10.1	12.4	41.0	5.4
Validation	*6.3*	*7.7*	*121.2*	*4.1*

- Forecasts constant value
  - Misses upward trend
- Spikes appear random

Strengths of the models

- Cat model
  - Accurately identifies the general shape of the population
  - Animal shelter is able to estimate when peaks are likely to occur
- Dog and other models
  - Models are more ‘boring’ but have lower errors, so less likely to be as significantly wrong as more complex models
  - Reasonable short term estimates but quickly outdated
    - Potentially could improve by re-running models more often

Weak points of the models

- Evaluation metrics
  - ‘Averaging’ models have lowest errors but forecast straight lines
  - Dog and other models not useful for capturing expected up and down periods
  - Potentially alternative evaluation metrics are required
- Random spikes
  - Almost impossible to predict
- Overfitting
  - Very likely with sliding windows cross validation
  - Difficult to combine the need for long training data periods and the decreasing usefulness of older data

Further work

Additional data
- Employment / economic data
- Animal health – perhaps using NLP techniques
- Intervention campaigns e.g. discounted adoption fees

Evaluation metrics
- Consider what desired outcome is
- Is underestimating worse than overestimating?

Different data
- Intake / Outtake
- The daily change (rather than absolute daily number)

Further hyperparameter tuning
- Prophet – holidays, specific changepoints
- NN / RF – several more options to consider

Further feature engineering
- Understand feature importances (look back periods, months / days)
- Use PCA to remove collinearity

Different models
- RNNs
- LSTM

Acknowledgements

- Technical advice and support gratefully received from
  - Jenny Yu
  - Tom Nickson
  - Technical Coaching and peer group via Slack

- References
  - Forecasting: Principles and Practice by Rob J Hyndman and George Athanasopoulos
- Icons
  - Icons made by OCHA and Freepik from www.flaticon.com