Using Neural Networks for Time-Series Prediction

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QuanTech NYC

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Outline

1. Introduce problem
2. Phrase problem as an ML problem
3. Collect and apply data
4. Select features
5. Train the model
6. Improve the model
7. Tips

Who am I?

Quantopian

- Works with storage and manipulation of time series data
- Integrates third-party data sets

The Problem

Osu!

Elements

Figure 1: A hit circle

Elements

Figure 1: A hit circle

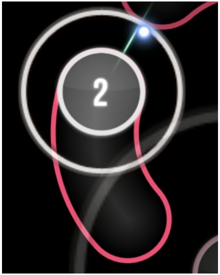


Figure 2: A slider

Elements

Figure 1: A hit circle

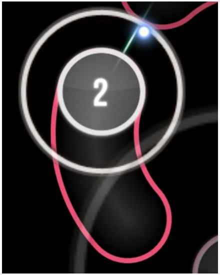


Figure 2: A slider

Figure 3: Mouse cursor

Osu! (cont.)

Scoring

300 points if on the beat

Osu! (cont.)

Scoring

300 points if on the beat

100 points if slightly off the beat

Osu! (cont.)

Scoring

300 points if on the beat

100 points if slightly off the beat

Osu! (cont.)

Scoring

300 points if on the beat

100 points if slightly off the beat

50 points if really off the beat

Osu! (cont.)

Scoring

300 points if on the beat

100 points if slightly off the beat

50 points if really off the beat

Osu! (cont.)

Scoring

300 points if on the beat

100 points if slightly off the beat

50 points if really off the beat

0 points for missing entirely

Osu! (cont.)

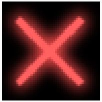
Scoring

300 points if on the beat

100 points if slightly off the beat

50 points if really off the beat

0 points for missing entirely



Osu! (cont.)

Sample

```
$ mpv videos/osu-example.avi
```

Problem

Improve my rank quickly

Problem

Improve my rank quickly

Many new songs a week

Problem

Improve my rank quickly

Many new songs a week

Songs award a variable amount of points

Problem

Improve my rank quickly

Many new songs a week

Songs award a variable amount of points

Particular playstyle

Problem

Improve my rank quickly

Many new songs a week

Songs award a variable amount of points

Particular playstyle

Arbitrage opportunity?

Phrasing the Problem

Problem

Predict my score on a beatmap

Problem

Predict my score on a beatmap

Need to compute accuracy %

Problem

Predict my score on a beatmap

- Need to compute accuracy %
- Temporal Accuracy

Problem

Predict my score on a beatmap

- Need to compute accuracy %
- Temporal Accuracy
- Aim Accuracy

Machine Learning Models

Classifiers
Label a sample as a member of one of a finite set of classes.

Regressors
Approximate a numerical function.

LSTM Models

Order dependent data

LSTM Models

Order dependent data

Sequence of observations

LSTM Models

Order dependent data

Sequence of observations

Uses windows of time-sorted observations

Our Problem

For each hit-object, predict..

Our Problem

For each hit-object, predict..

Classifier
A label.

- 300
- 100
- 50
- 0 (miss)

Our Problem

For each hit-object, predict..

Classifier
A label.

- 300
- 100
- 50
- 0 (miss)

Regressor
A numeric error metric.

1. Aim Error ((x, y) error)
2. Accuracy Error (punctuality)

Data Collection

Beatmaps

Hit objects in (x, y, time) space.

Beatmaps

Hit objects in (x, y, time) space.

Circle Size (CS)

Beatmaps

Hit objects in (x, y, time) space.

Circle Size (CS)

Approach Rate (AR)

Beatmaps

Hit objects in (x, y, time) space.

Circle Size (CS)

Approach Rate (AR)

Overall Difficulty (OD) (score thresholds)

Raw Data

Beatmap

```
[HitObjects]
103,272,52926,6,0,L|111:176,1,67.5000025749208
93,95,53279,1,2,0:3:0:0:
194,131,53455,2,0,B|263:160|264:100|337:135,1,135.00000514
437,204,53985,2,0,L|432:286,1,67.5000025749208
394,105,54338,6,0,L|399:17,1,67.5000025749208
286,62,54690,1,2,0:3:0:0:
177,54,54867,2,0,B|110:74|110:30|41:53,1,135.000005149842,
70,213,55396,2,0,L|77:132,1,67.5000025749208
161,215,55749,6,0,P|175:273|247:314,1,135.000005149842,0|2
341,286,56279,1,0,0:0:0:0:
308,183,56455,2,0,P|268:201|245:238,1,67.5000025749208,0|2
```

Mods

- Hard Rock (HR)

Mods

- Hard Rock (HR)
- Double Time (DT)

Mods

- Hard Rock (HR)
- Double Time (DT)
- Hidden (HD)

Mods

- Hard Rock (HR)
- Double Time (DT)
- Hidden (HD)
- etc...

Replays

Time series of...

Replays

Time series of...

Cursor location

Replays

Time series of...

- Cursor location
- Keyboard state

Replays

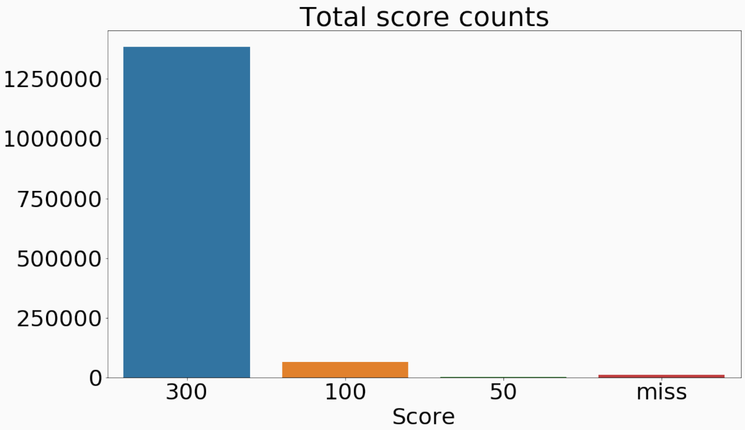
I had about seven years of replays laying around!

Understanding our data

Accuracy thresholds (milliseconds)

OD	300	100	50
1	73.5	131.5	189.5
2	67.5	123.5	179.5
3	61.5	115.5	169.5
4	55.5	107.5	159.5
5	49.5	99.5	149.5
6	43.5	91.5	139.5
7	37.5	83.5	129.5
8	31.5	75.5	119.5
9	25.5	67.5	109.5
10	19.5	59.5	99.5

Understanding our data (cont.)



Prediction Targets

Joining Data

Prediction Targets

Joining Data

Find all clicks by taking times where key state changes

Prediction Targets

Joining Data

Find all clicks by taking times where key state changes

Match click with the nearest hit object (ignores hit locking!)

Prediction Targets

Accuracy Error

Absolute difference in time.

Prediction Targets

Accuracy Error

Absolute difference in time.

Comparable across different OD

Prediction Targets

Aim Error

Euclidean distance between click and center of circle.

Prediction Targets

Aim Error

Euclidean distance between click and center of circle.

Comparable across different CS

Feature Selection

What is a feature?

Numeric inputs to the ML model

What is a feature?

Numeric inputs to the ML model

What are we observing

What is a feature?

Numeric inputs to the ML model

- What are we observing
- Focus the model on aspects of the data

What is a feature?

Numeric inputs to the ML model

- What are we observing
- Focus the model on aspects of the data
- Chance to use domain knowledge

Raw Data

Beatmap

```
[HitObjects]
103,272,52926,6,0,L|111:176,1,67.5000025749208
93,95,53279,1,2,0:3:0:0:
194,131,53455,2,0,B|263:160|264:100|337:135,1,135.00000514
437,204,53985,2,0,L|432:286,1,67.5000025749208
394,105,54338,6,0,L|399:17,1,67.5000025749208
286,62,54690,1,2,0:3:0:0:
177,54,54867,2,0,B|110:74|110:30|41:53,1,135.000005149842,
70,213,55396,2,0,L|77:132,1,67.5000025749208
161,215,55749,6,0,P|175:273|247:314,1,135.000005149842,0|2
341,286,56279,1,0,0:0:0:0:
308,183,56455,2,0,P|268:201|245:238,1,67.5000025749208,0|2
```

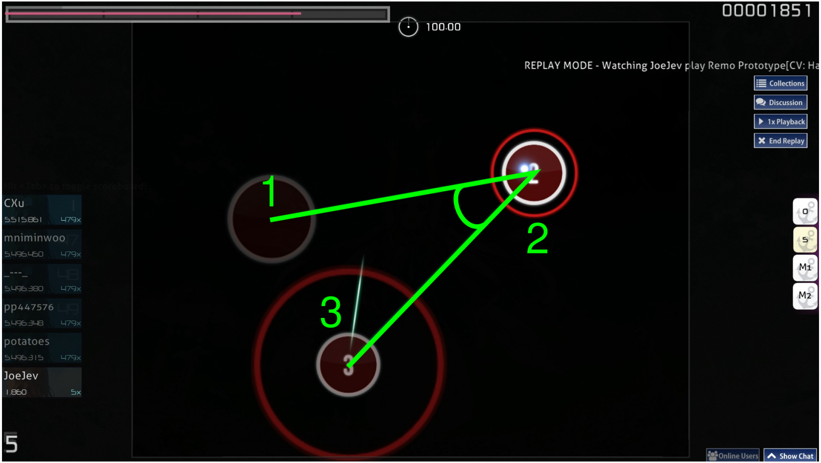
Simple Features

absolute_x

absolute_y

absolute_time

Domain Specific Features



Windows

time	x	y
00:37.366	372	94
00:37.763	447	205
00:38.027	217	299
00:38.291	229	171
00:38.424	274	358
00:38.688	149	221
00:38.952	330	186
00:39.217	233	127
00:39.481	233	127
00:39.613	198	303

Windows

time	x	y
00:37.366	372	94
00:37.763	447	205
00:38.027	217	299
00:38.291	229	171
00:38.424	274	358
00:38.688	149	221
00:38.952	330	186
00:39.217	233	127
00:39.481	233	127
00:39.613	198	303

Windows

time	x	y
00:37.366	372	94
00:37.763	447	205
00:38.027	217	299
00:38.291	229	171
00:38.424	274	358
00:38.688	149	221
00:38.952	330	186
00:39.217	233	127
00:39.481	233	127
00:39.613	198	303

Windows

time	x	y	relative x	relative y
00:37.366	372	94	-	-
00:37.763	447	205	298	-16
00:38.027	217	299	68	78
00:38.291	229	171	80	-50
00:38.424	274	358	125	137
00:38.688	149	221	0	0
00:38.952	330	186	181	-35
00:39.217	233	127	84	-94
00:39.481	233	127	-	-
00:39.613	198	303	-	-

Windows

time	x	y	relative x	relative y
00:37.366	372	94	-	-
00:37.763	447	205	-	-
00:38.027	217	299	-113	113
00:38.291	229	171	-101	-15
00:38.424	274	358	-56	172
00:38.688	149	221	-181	35
00:38.952	330	186	0	0
00:39.217	233	127	-97	-59
00:39.481	233	127	-97	-59
00:39.613	198	303	-	-

Windows

time	x	y	relative x	relative y
00:37.366	372	94	-	-
00:37.763	447	205	-	-
00:38.027	217	299	-	-
00:38.291	229	171	-4	44
00:38.424	274	358	41	231
00:38.688	149	221	-84	94
00:38.952	330	186	97	59
00:39.217	233	127	0	0
00:39.481	233	127	0	0
00:39.613	198	303	-35	176

Osu! Features

- `absolute_x`
- `absolute_y`
- `absolute_time`
- `relative_x`
- `relative_y`
- `relative_time`
- `is_slider_tick`
- `approach_rate`
- `distance_from_previous`
- `distance_to_next`
- `pitch`
- `roll`
- `yaw`

Training

Input Shapes

Feature array shape

(, , ,)

Input Shapes

Feature array shape

(, , number of features,)

Input Shapes

Feature array shape

(, window length, number of features,)

Input Shapes

Feature array shape

(number of windows, window length, number of features,)

Input Shapes

Feature array shape

(number of windows, window length, number of features,)

Label array shape

(number of windows,)

(number of windows,)

Keras

```
input_ = keras.layers.Input(
    shape=(window_length, len(features))
)
```

Keras

```
input_ = keras.layers.Input(
    shape=(window_length, len(features))
)
lstm = keras.layers.LSTM(lstm_layer_size)(input_)
```

Keras

```
input_ = keras.layers.Input(
    shape=(window_length, len(features))
)
lstm = keras.layers.LSTM(lstm_layer_size)(input_)
aim_error = keras.layers.Dense(
    1,
    activation='linear',
    name='aim_error',
)(lstm)
```

Keras

```
input_ = keras.layers.Input(
    shape=(window_length, len(features))
)
lstm = keras.layers.LSTM(lstm_layer_size)(input_)
aim_error = keras.layers.Dense(
    1,
    activation='linear',
    name='aim_error',
)(lstm)
accuracy_error = keras.layers.Dense(
    1,
    activation='linear',
    name='accuracy_error',
)(lstm)
```

Keras (cont.)

```
model = keras.models.Model(
    inputs=input_,
    outputs=[aim_error, accuracy_error],
)
```

Keras (cont.)

```
model = keras.models.Model(
    inputs=input_,
    outputs=[aim_error, accuracy_error],
)
model.compile(
    loss='mse',
    optimizer='rmsprop',
)
```

Keras (cont.)

```
# compute features, aim_error, accuracy_error
model.fit(
    features,
    {
        'aim_error': aim_error,
        'accuracy_error': accuracy_error,
    },
)
```

Keras (cont.)

```python
# compute features, aim_error, accuracy_error
model.fit(
    features,
    {
        'aim_error': aim_error,
        'accuracy_error': accuracy_error,
    },
)

model.predict(features)
```

How does it look?

How does it look?

bad

Feature Scaling

Sensitive to input ranges

Feature Scaling

Sensitive to input ranges

```
(data - data.mean()) / data.std()
```

Feature Scaling

Sensitive to input ranges

```
(data - data.mean()) / data.std()
```

Save the mean and std of the training data!

Data (again)

```
features:
    absolute_x:
      mean: 256.93
      std:  581144.54
      min:  -26.25
      max:  4297802023696 4152.0
    absolute_y:
      mean: 188.67
      std:  96280.10
      min:  -12.20
      max:  10754663190171874.0
```

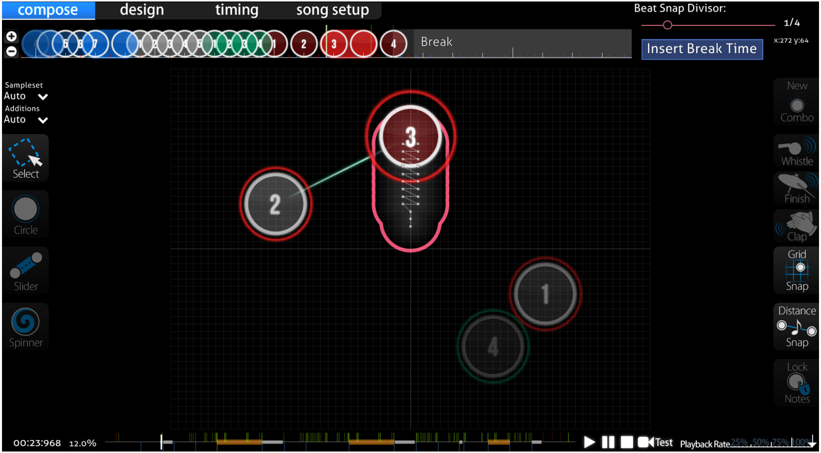
Data (again)

osu! playfield:

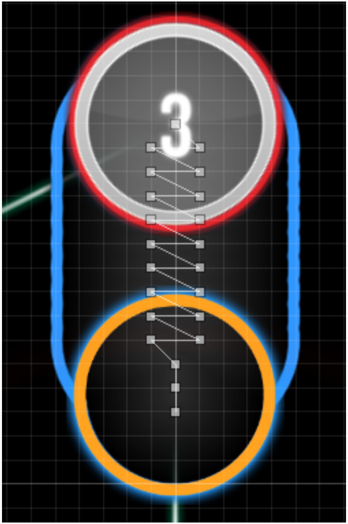
(512, 384)

```
features:
    absolute_x:
      mean: 256.93
      std:  581144.54
      min:  -26.25
      max:  4297802036964152.0
    absolute_y:
      mean: 188.67
      std:  96280.10
      min:  -12.20
      max:  1075466319017187 4.0
```

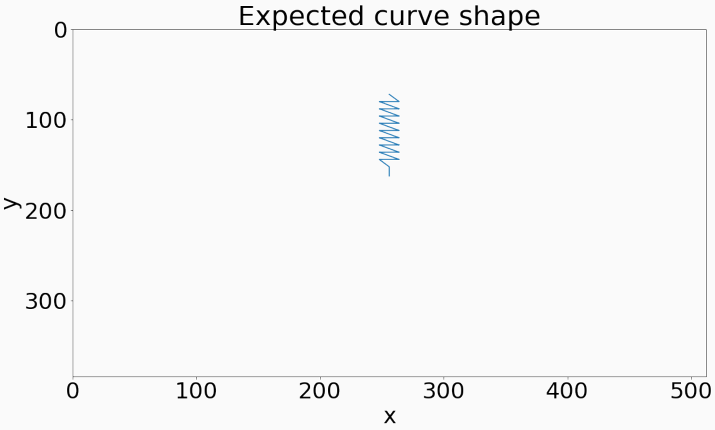
Slider Curves



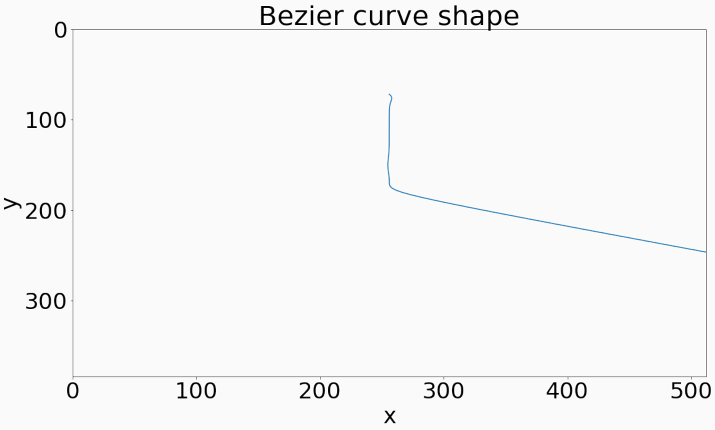
Slider Curves



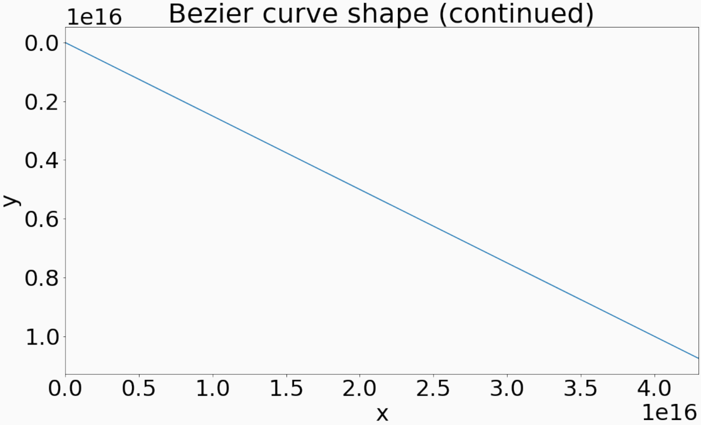
Slider Curves



Slider Curves



Slider Curves



Understanding our data

Accuracy thresholds (milliseconds)

OD	300	100	50
1	73.5	131.5	189.5
2	67.5	123.5	179.5
3	61.5	115.5	169.5
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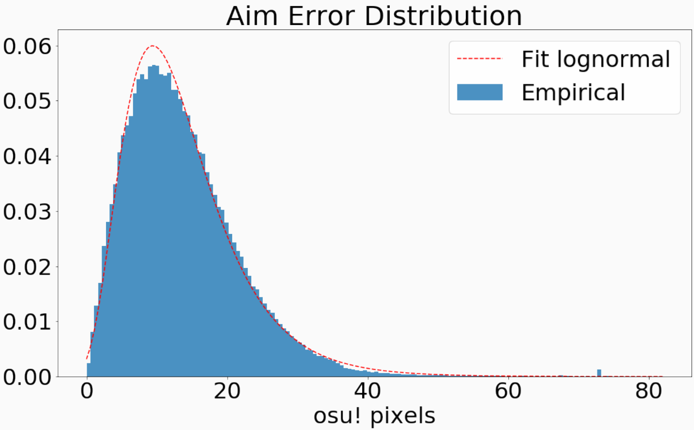
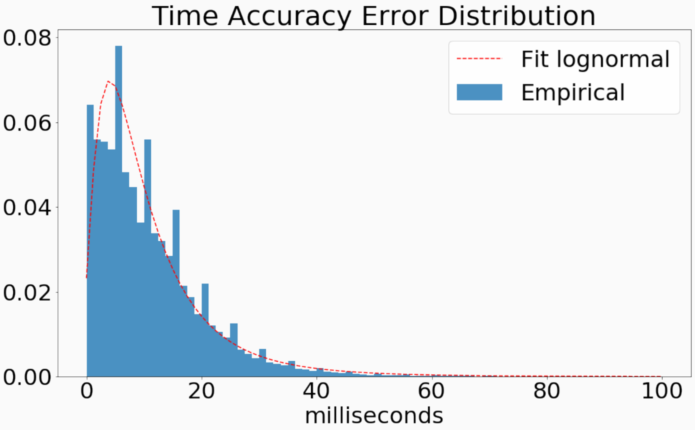
7	37.5	83.5	129.5
8	31.5	75.5	119.5
9	25.5	67.5	109.5
10	19.5	59.5	99.5

Data (again)



Aim Error Distribution
Fit lognormal
Empirical
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
20
40
60
80
osu! pixels

Data (again)

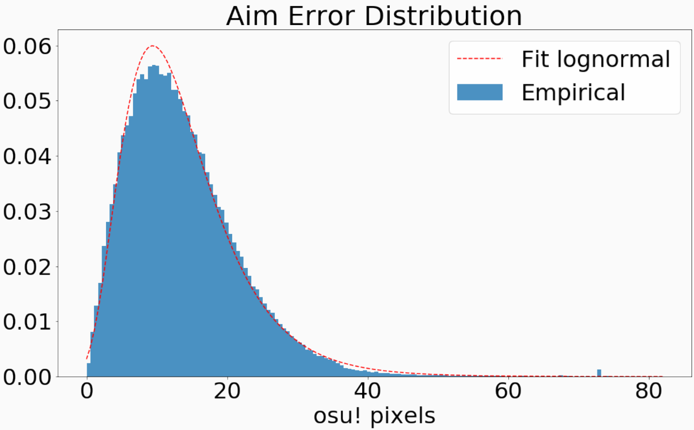


Time Accuracy Error Distribution
Fit lognormal
Empirical
0.08
0.06
0.04
0.02
0.00
0
20
40
60
80
100
milliseconds

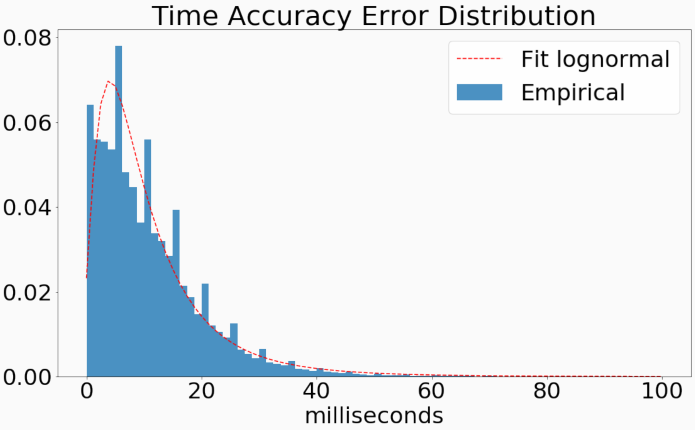
Fit a distribution

`lain/lstm.py:605`

Sample Weights



Sample Weights



Sample Weights (cont.)

```
model.fit(
    ...
    sample_weight={
        'aim_error:': aim_error_weights,
        'accuracy_error': accuracy_error_weights,
    },
)
```

Pessimism

Model thinks I am too good

Pessimism

Model thinks I am too good

Bias in data collection

Pessimism

Model thinks I am too good

Bias in data collection

Raise errors to a pre-decided power (1.1)

Pessimism

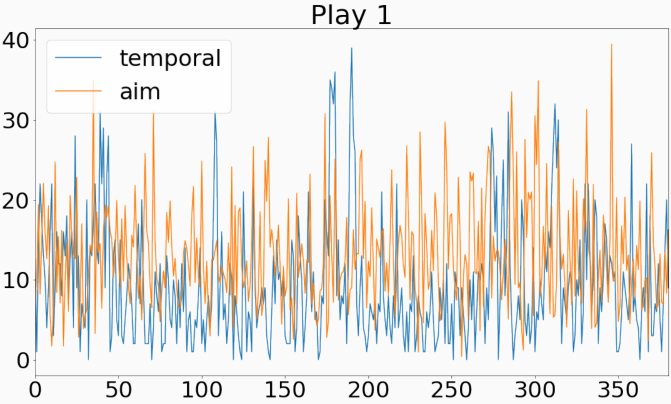
Model thinks I am too good

Bias in data collection

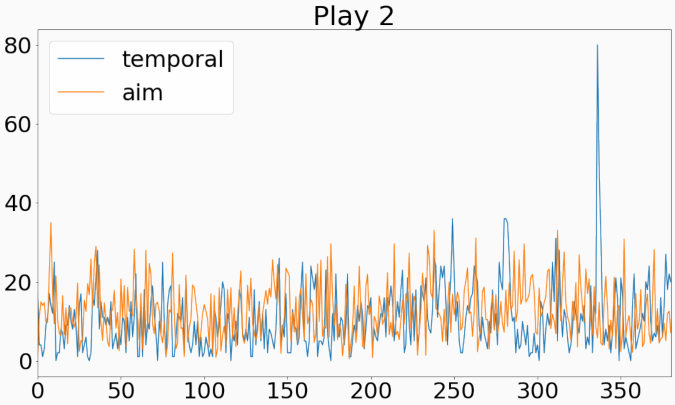
Raise errors to a pre-decided power (1.1)

This is made up nonsense

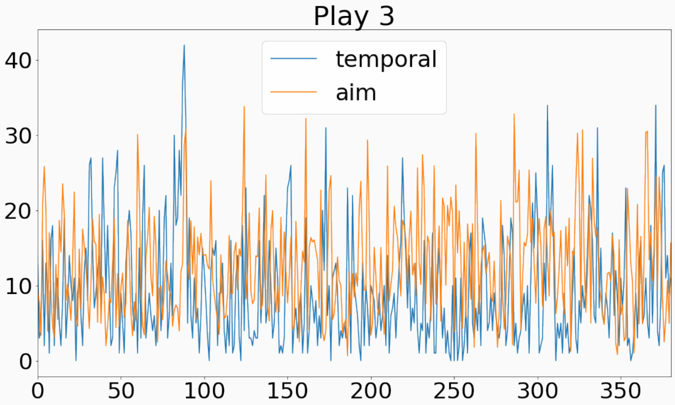
Example Output



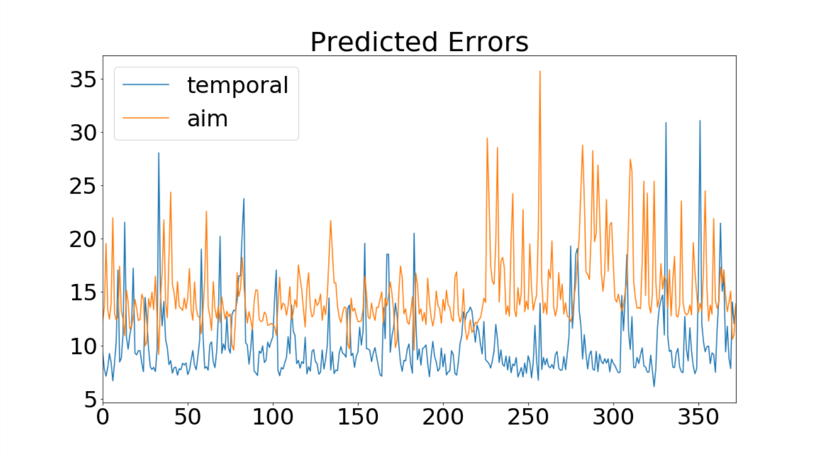
Example Output



Example Output



Example Output



Example Output (cont.)

Song	Stars	Predicted	Actual
CHiCO with HoneyWorks - Wolf	5.34	99.85%	99.13%
CHiCO with HoneyWorks - Wolf	5.34	99.85%	99.08%
CHiCO with HoneyWorks - Wolf	5.34	99.85%	98.51%
mimimemeMIMI - Sayonara Usotsuki	5.70	98.38%	98.68%
Kanon Wakeshima - Tsukinami	5.82	99.12%	99.87%

Tips

Understanding the process

`verbose` flags that log information

Understanding the process

`verbose` flags that log information

progress indicators (`click.progressbar`)

Understanding the process

`verbose` flags that log information

progress indicators (`click.progressbar`)

print summary statistics early in process

Software Engineering Matters

Group code into a domain-aware `Model` class.

Software Engineering Matters

Group code into a domain-aware `Model` class.

- feature extraction

Software Engineering Matters

Group code into a domain-aware `Model` class.

- feature extraction
- feature scaling

Software Engineering Matters

Group code into a domain-aware `Model` class.

- feature extraction
- feature scaling
- label extraction

Software Engineering Matters

Group code into a domain-aware `Model` class.

- feature extraction
- feature scaling
- label extraction
- managing keras

Serialization

save models to disk

Serialization

save models to disk

train on ec2 and use locally

Serialization

save models to disk

train on ec2 and use locally

train locally then deploy

Serialization

save models to disk

train on ec2 and use locally

train locally then deploy

supported by keras

Key Points

1. Most of the work is before or after keras

Key Points

1. Most of the work is before or after keras
2. Understand the data and the data collection processes

Key Points

1. Most of the work is before or after keras
2. Understand the data and the data collection processes
3. Osu! is a fun game

Thank You

Questions?

`github.com/llllllllll` **(10 lowercase L's)**

- `/lain` (model implementation)
- `/slider` (tools for working with osu! data and API)
- `/combine` (irc server running lain-as-a-service)