Click-Through Rate Prediction

Problem and Data

Click-Through Rate Prediction

Let's consider an automatic recommendation problem

- Given a set of restaurant indexed on a a web platform (think Tripadvisor)
- ...We want to estimate how likely a user is to actually open the restaurant card

This is know as click-through rate

This example (and the approach) is based on this TensorFlow Lattice Tutorail

Loading the Data

We are going to use a synthetic dataset for this use case

In [6]:
```
tr, val, ts = util.load_restaurant_data()
dt_in = tr.columns[:-1]
tr.iloc[:4]
```

Out[6]:

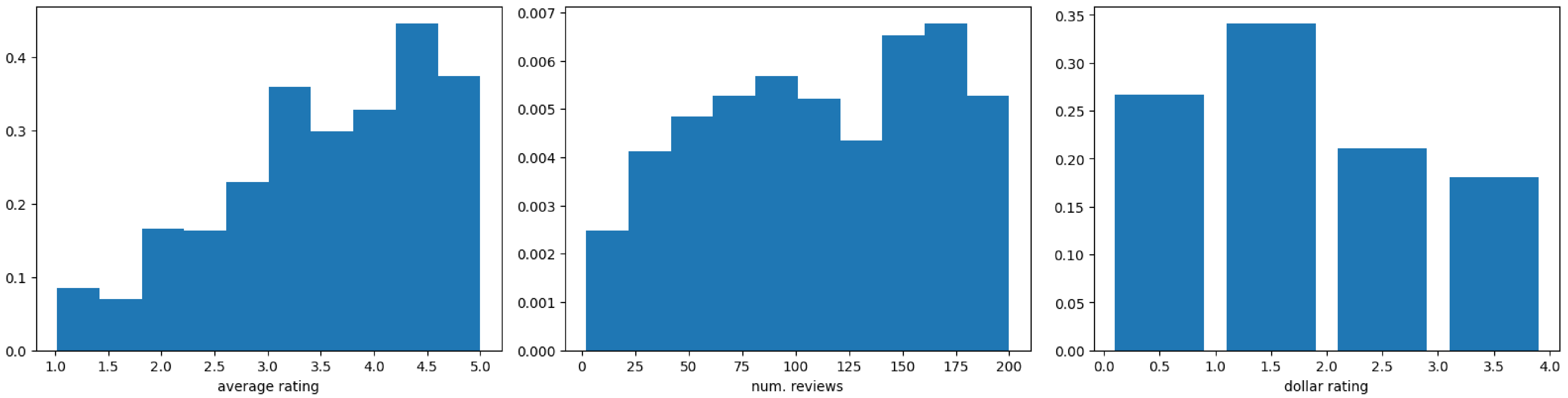
	avg_rating	num_reviews	dollar_rating	clicked
0	3.927976	122.0	DDDD	1
1	3.927976	122.0	DDDD	0
2	3.927976	122.0	DDDD	0
3	4.329771	122.0	DDDD	1

- `avg_rating` is the average rating of the reviews for this restaurant
- `num_reviews` is the number of said reviews
- `dollar_rating` tells us how expensive the restaurant is
- `clicked` tells use whether a use actually click on the card, when it was displayed

Data Distribution

Let's check the attribute distribution on the training set

```
In [7]: util.plot_ctr_distribution(tr, figsize=figsize, nbins=10)
```

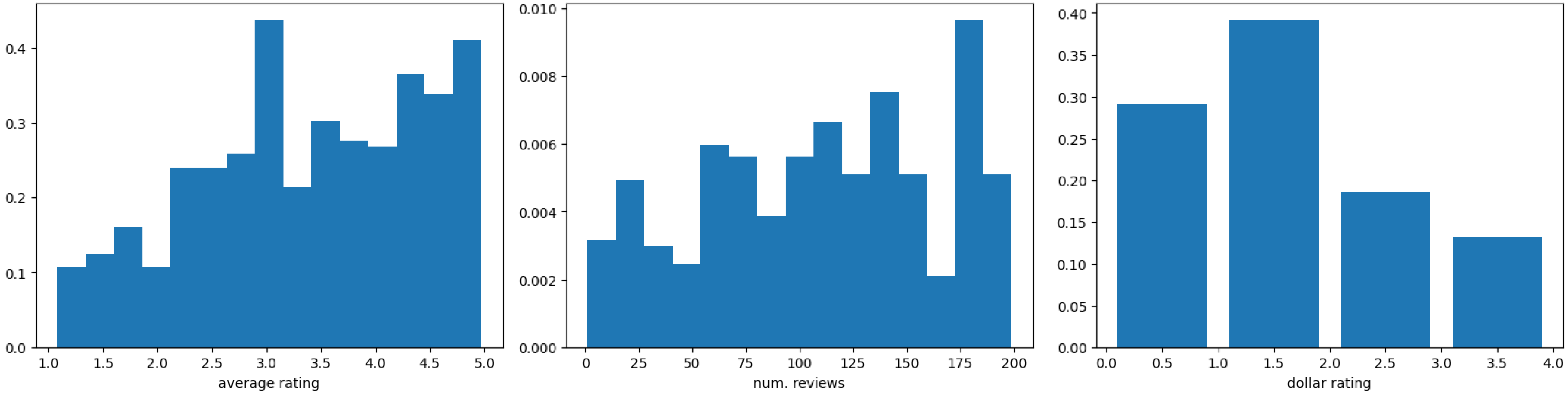


- Most restaurants in our dataset have a good rating
- The number of review is close to unifor
- Most restaurants are in the mid-low tier in terms of price

Data Distribution

...Then on a second dataset, that we are going to use for testing

In [8]:
```
util.plot_ctr_distribution(val, figsize=figsize)
```



- In truth, this dataset is mean to be a validation set
- ...But for now we are going to treat it as a test set
- We will revisit this use case later in the course and understand the reason

Loading the Data

Not all users have the same preferences

...So, when presented with the same restaurant may make opposite decisions:

```
In [9]: tr[(tr[dt_in] == tr.iloc[4][dt_in]).all(axis=1)]
```

Out[9]:

	avg_rating	num_reviews	dollar_rating	clicked
4	3.099026	118.0	DD	0
5	3.099026	118.0	DD	1
6	3.099026	118.0	DD	1
7	3.099026	118.0	DD	1
8	3.099026	118.0	DD	1

- Every row correspontds to a restaurant visualization event
- ...And, therefore, many input vectors in the dataset are duplicated
- The `clicked` column may be either 1 or 0 in these cases

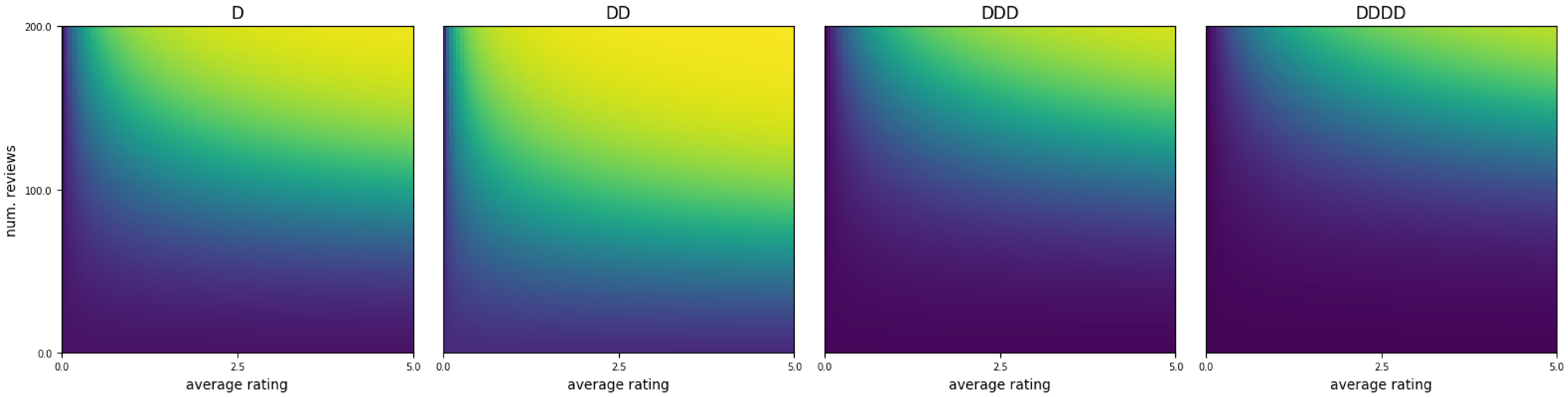
Formally, we are studying a stochastic process

Target Function

However, what we want to learn is the probability of a click

We know exactly how that changes, since we are working with synthetic data

In [10]:
```
util.plot_ctr_truth(figsize=figsize)
```



...But of course we'll pretend we don't have this information

Click-Through Rate Prediction

Problem Formalization

A System Model

Let's start by modeling the system

We can view both the restaurant information an the clicks as random variables:

- X, representing the restaurant information
- Y, representing the act of clicking (1 = click, 0 = no click)

The two variables are related

We can model this formally via their joint distribution:

$$X, Y \sim P(X, Y)$$

We want to learn the probability of clicking, given observed restaurant information

In other words, the conditional probability:

$$P(Y \mid X)$$

Our Data

Our training data consists of a collection of examples $\{x_i, y_i\}_{i=1}^{m}$

- x_i is the restaurant data for on visualization event
- $y_i = 1$ if the user clicked, and 0 otherwise

Say that we try to learn an approximatation $\hat{f}(x;\theta)$ for $P(Y \mid X)$

In this case, training for maximum likelihood estimation means solving:

$$\operatorname*{argmax}_{\theta} \prod_{i=1}^{m} y_i \hat{f}(x_i;\theta) + (1-y_i)(1-\hat{f}(x_i;\theta))$$

- The estimated probability should be high in case of clicks (i.e. $y_i = 1$)
- ...And low in case of non-clicks (i.e. $1 - y_i$)

This is (almost) exactly how most classifiers are trained

With most types of ML techniques...

When you train a classifier
...You are actually training a probabilistic model

Click-Through Rate Prediction

A Solution Approach

Preparing the Data

We will start by tackling the problem using a Multi Layer Perceptron

We normalize the numeric data:

In [13]:
```
nf = ['avg_rating', 'num_reviews']
scale = tr[nf].max()
tr_s = tr.copy()
tr_s[nf] = tr_s[nf] / scale
val_s = val.copy()
val_s[nf] = val_s[nf] / scale
ts_s = ts.copy()
ts_s[nf] = ts_s[nf] / scale
```

We also adopt a one-hot encoding for the categorical data:

In [14]:
```
tr_sc = pd.get_dummies(tr_s).astype(np.float32)
val_sc = pd.get_dummies(val_s).astype(np.float32)
ts_sc = pd.get_dummies(ts_s).astype(np.float32)
dt_in_c = [c for c in tr_sc.columns if c != 'clicked']
```

Preparing the Data

Here is the result of our preparation

In [15]:
```
tr_sc
```

Out[15]:

	avg_rating	num_reviews	clicked	dollar_rating_D	dollar_rating_DD	dollar_rating_DDD	dollar_rating_DDDD
0	0.785773	0.610	1.0	0.0	0.0	0.0	1.0
1	0.785773	0.610	0.0	0.0	0.0	0.0	1.0
2	0.785773	0.610	0.0	0.0	0.0	0.0	1.0
3	0.866150	0.610	1.0	0.0	0.0	0.0	1.0
4	0.619945	0.590	0.0	0.0	1.0	0.0	0.0
...	...	...	...	...	...	...	...
830	0.597304	0.055	1.0	0.0	1.0	0.0	0.0
831	0.783784	0.505	1.0	1.0	0.0	0.0	0.0
832	0.783784	0.505	1.0	1.0	0.0	0.0	0.0
833	0.688336	0.270	1.0	0.0	1.0	0.0	0.0
834	0.688336	0.270	0.0	0.0	1.0	0.0	0.0

835 rows × 7 columns

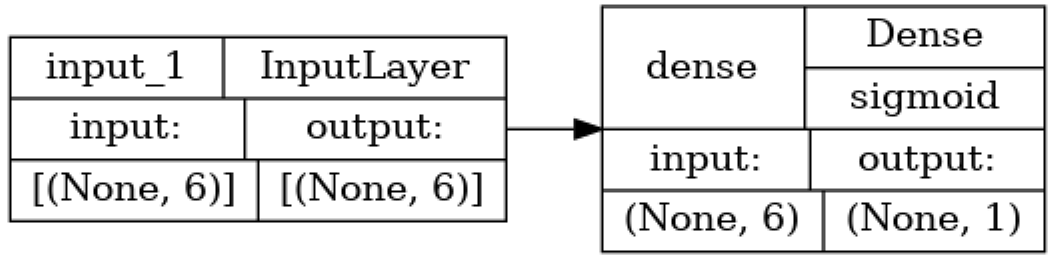
Building a Baseline Model

Our model will be a simple Neural Network

In particular we will use a Logistic Regressor, plus a deeper model

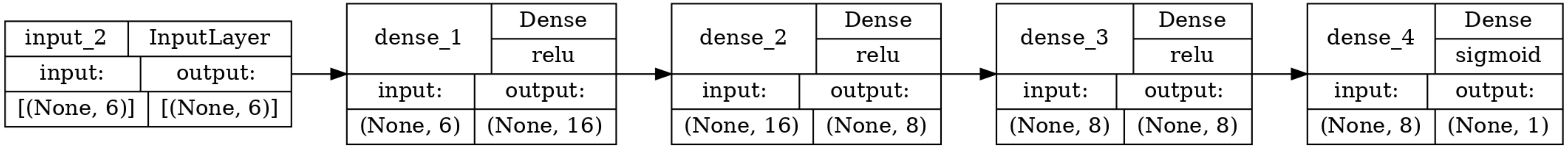
In [16]:
```
nn = util.build_nn_model(input_shape=len(dt_in_c), output_shape=1, hidden=[], output_a
util.plot_nn_model(nn, dpi=96)
```

Out[16]:



In [17]:
```
nn2 = util.build_nn_model(input_shape=len(dt_in_c), output_shape=1, hidden=[16, 8, 8],
util.plot_nn_model(nn2, dpi=150)
```

Out[17]:



Training the Baseline Model

We'll train both models to convergence

```
In [18]: nn = util.build_nn_model(input_shape=len(dt_in_c), output_shape=1, hidden=[], output_a
         history = util.train_nn_model(nn, tr_sc[dt_in_c], tr_sc['clicked'], loss='binary_cross
         util.plot_training_history(history, figsize=(figsize[0], 0.5 * figsize[1]), display_lo
```

```
Final loss: 0.5117 (training)
```

```
In [19]: nn2 = util.build_nn_model(input_shape=len(dt_in_c), output_shape=1, hidden=[16, 8, 8],
         history = util.train_nn_model(nn2, tr_sc[dt_in_c], tr_sc['clicked'], loss='binary_cros
         util.plot_training_history(history, figsize=(figsize[0], 0.5 * figsize[1]), display_lo
```

```
Final loss: 0.4939 (training)
```

- More shallow models require more training iterations to reach convergence via gradient descent
- On the other hand, deeper models require more computational effort per evaluation

Evaluating the Predictions

This is not a classification problem, so accuracy is not a good metric

- The output of our system is meant to be interpreted as a probability
- ...So, rounding to obtain a deterministic prediction may be too restrictive

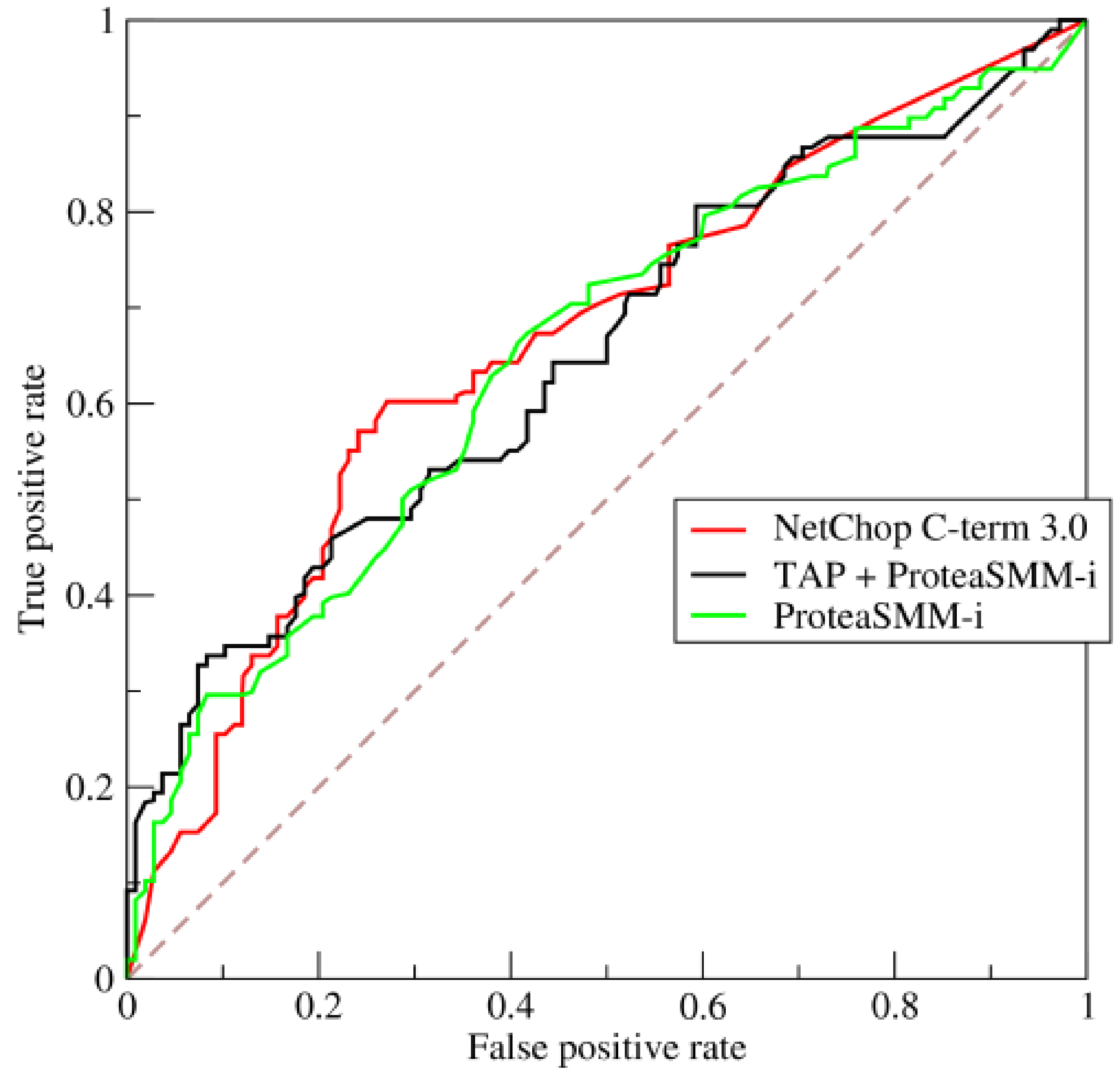
Instead, we will make a first evaluation using a ROC curve

A Receiver Operating Characteristic curve is a type of plot

- We consider multiple threshold values
  - Each threshold is meant to be used for discriminating between classes
  - The usual rounding approach is equivalent to a 0.5 threshold
- On the x axis, we report the false positive rate for each threshold
- On the y axis, we report the true positive rate for each threshold

Evaluating the Predictions

A ROC curve looks like this (image from wikipedia)



- The large the Area Under Curve (AUC), the better the performance
- The AUC value is guaranteed to be in the $[0, 1]$ interval

Evaluating the Predictions

Let's compute the AUC values for the two sets we are focusing on

In [20]:
```
pred_tr = nn.predict(tr_sc[dt_in_c], verbose=0)
pred_val = nn.predict(val_sc[dt_in_c], verbose=0)
auc_tr = roc_auc_score(tr_sc['clicked'], pred_tr)
auc_val = roc_auc_score(val_sc['clicked'], pred_val)
print(f'AUC score for the Logistic Regressor: {auc_tr:.2f} (training), {auc_val:.2f} (
```

```
AUC score for the Logistic Regressor: 0.80 (training), 0.81 (test)
```

In [21]:
```
pred_tr2 = nn2.predict(tr_sc[dt_in_c], verbose=0)
pred_val2 = nn2.predict(val_sc[dt_in_c], verbose=0)
auc_tr2 = roc_auc_score(tr_sc['clicked'], pred_tr2)
auc_val2 = roc_auc_score(val_sc['clicked'], pred_val2)
print(f'AUC score for the deeper NN: {auc_tr2:.2f} (training), {auc_val2:.2f} (test)')
```

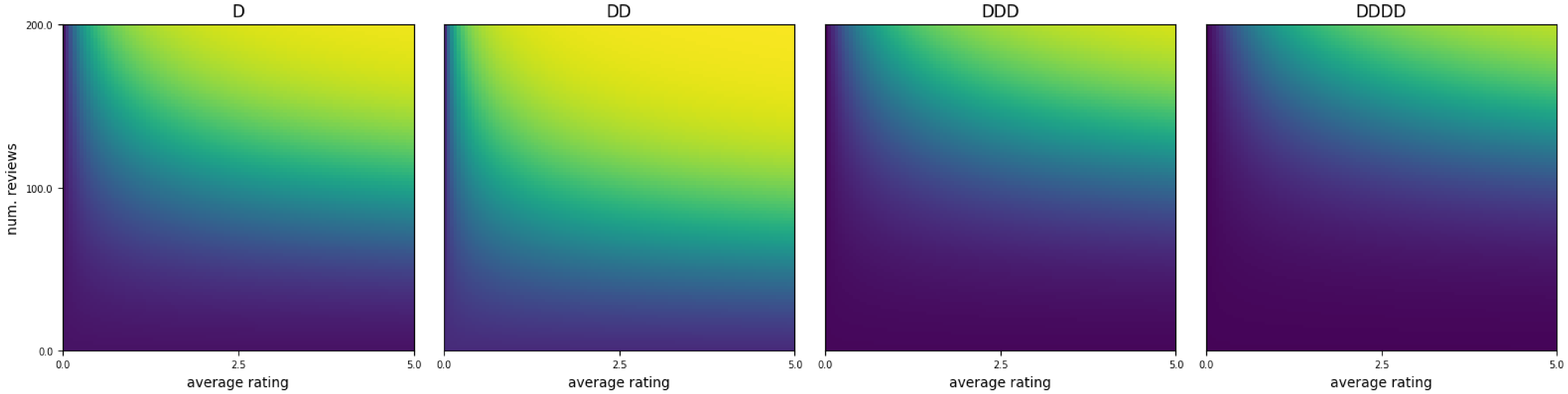
```
AUC score for the deeper NN: 0.81 (training), 0.80 (test)
```

- Both models work reasonably well on both the training and the test data

Checking the Learned Response Surfaces

Here we have again the ground truth for our click rate

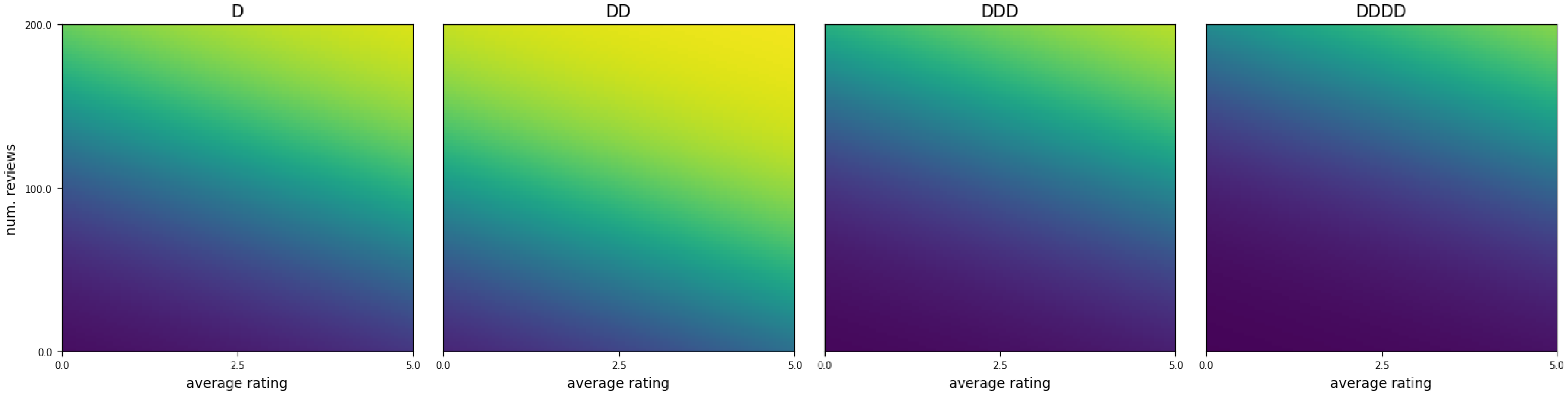
```
In [22]: util.plot_ctr_truth(figsize=figsize)
```



Checking the Learned Response Surfaces

Here is the full response surface for the Logistic Regressor

In [23]:
```
util.plot_ctr_estimation(nn, scale, figsize=figsize)
```



Checking the Learned Response Surfaces

Here is the full response surface for the deeper NN

In [24]:
```
util.plot_ctr_estimation(nn2, scale, figsize=figsize)
```