Fairness Issues in Machine Learning

Fairness Issues in Machine Learning

Say we want to estimate the risk of violent crimes in given population

- This is obviously a very ethically sensitive (and questionable) task
- Our model may easily end up discriminating some social groups

Which makes it a good test case for fairness issues in data-driven models

Loading and Preparing the Dataset

We will start by loading the "crime" UCI dataset

We will use a pre-processed version made available by our support module:

In [2]:
```
data = cst.load_communities_data(data_folder)
attributes = data.columns[3:-1]
target = data.columns[-1]
data
```

Out[2]:

	communityname	state	fold	pop	race	pct12-21	pct12-29	pct16-24	pct65up	pctUrban	...	pctForeignBorn	pctBornStateR
1008	EastLampetertownship	PA	5	11999	0	0.1203	0.2544	0.1208	0.1302	0.5776	...	0.0288	0.8132
1271	EastProvidencecity	RI	6	50380	0	0.1171	0.2459	0.1159	0.1660	1.0000	...	0.1474	0.6561
1936	Betheltown	CT	9	17541	0	0.1356	0.2507	0.1138	0.0804	0.8514	...	0.0853	0.4878
1601	Crowleycity	LA	8	13983	0	0.1506	0.2587	0.1234	0.1302	0.0000	...	0.0029	0.9314
293	Pawtucketcity	RI	2	72644	0	0.1230	0.2725	0.1276	0.1464	1.0000	...	0.1771	0.6363
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1758	RockyMountcity	NC	8	48997	0	0.1454	0.2653	0.1247	0.1190	1.0000	...	0.0077	0.8138
1822	Amarillocity	TX	9	157615	0	0.1391	0.2660	0.1244	0.1085	1.0000	...	0.0412	0.6651
2207	WestHaventown	CT	10	54021	0	0.1186	0.2772	0.1318	0.1339	1.0000	...	0.0837	0.7031
1081	Humblecity	TX	5	12060	0	0.1545	0.3184	0.1530	0.0719	1.0000	...	0.0638	0.5983
1867	VanBurencity	AR	9	14979	0	0.1539	0.2826	0.1288	0.1078	1.0000	...	0.0210	0.6810

1993 rows × 101 columns

Loading and Preparing the Dataset

We prepare for normalizing all numeric attributes

- The only categorical input is "race" (0 = primarily white, 1 = primarily black)
- Incidentally, "race" is a natural focus to check for discrimination

We define the train-test divide and we identify the numerical inputs

In [3]:
```
tr_frac = 0.8 # 80% data for training
tr_sep = int(len(data) * tr_frac)
nf = [a for a in attributes if a != 'race'] + [target]
```

We compute the normalization constants and we transform the data

In [5]:
```
tmp = data.iloc[:tr_sep]
scale = tmp[nf].max()
sdata = data.copy()
sdata[nf] /= scale[nf]
# VConver
sdata[attributes] = sdata[attributes].astype(np.float32)
sdata[target] = sdata[target].astype(np.float32)
```

Loading and Preparing the Dataset

Finally we can separate the training and test set

In [6]:
```
tr = sdata.iloc[:tr_sep]
ts = sdata.iloc[tr_sep:]
tr.describe()
```

Out[6]:

	fold	pop	race	pct12-21	pct12-29	pct16-24	pct65up	pctUrban	medIncome
count	1594.000000	1594.000000	1594.000000	1594.000000	1594.000000	1594.000000	1594.000000	1594.000000	1594.000000
mean	5.515056	0.007309	0.031995	0.266962	0.398600	0.230577	0.226739	0.695383	0.272795
std	2.912637	0.030287	0.176042	0.084005	0.090329	0.098553	0.091256	0.445105	0.108972
min	1.000000	0.001368	0.000000	0.084191	0.134635	0.075644	0.031457	0.000000	0.104413
25%	3.000000	0.001943	0.000000	0.225230	0.350689	0.185238	0.167614	0.000000	0.190973
50%	5.000000	0.003035	0.000000	0.250919	0.385173	0.205575	0.223138	1.000000	0.249509
75%	8.000000	0.005922	0.000000	0.283824	0.419908	0.235735	0.275298	1.000000	0.334641
max	10.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

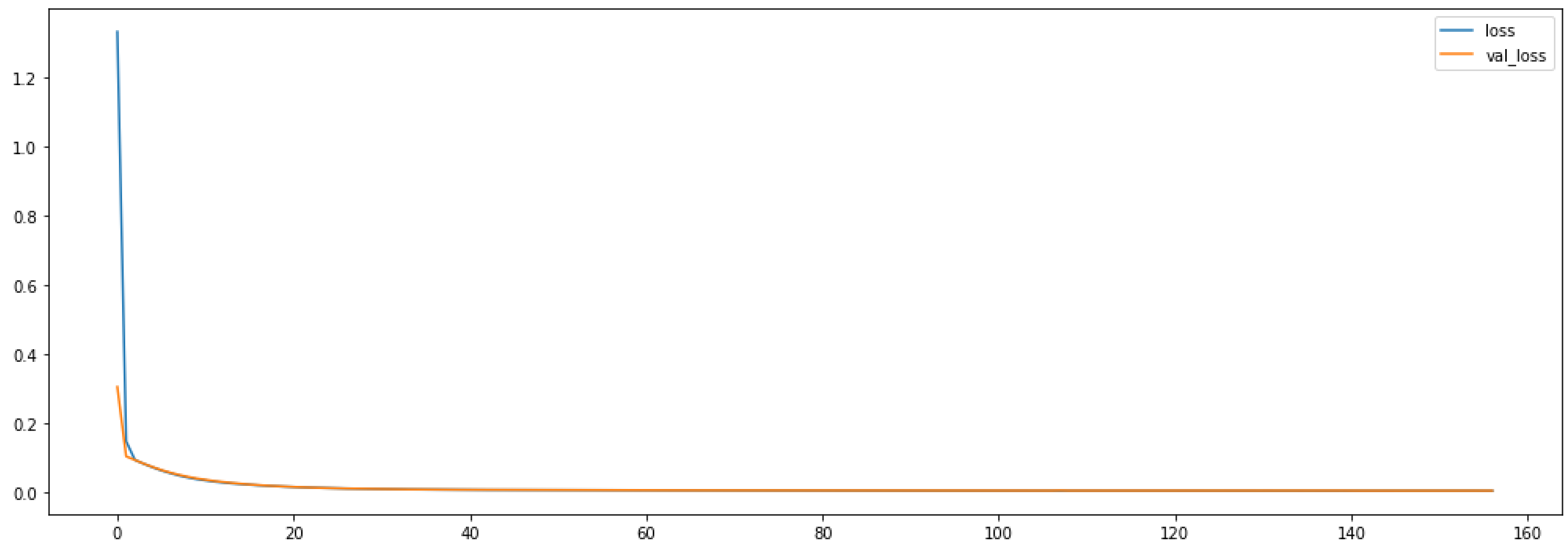
8 rows × 99 columns

Baseline

Let's establish a baseline by tackling the task via Linear Regression

In [8]:

```
nn = cst.MLPRegressor(input_shape=len(attributes), hidden=[])
nn.compile(optimizer='Adam', loss='mse')
cb = [callbacks.EarlyStopping(patience=10, restore_best_weights=True)]
history = nn.fit(tr[attributes], tr[target], batch_size=32, epochs=200, verbose=0,
                 validation_split=0.2, callbacks=cb)
cst.plot_training_history(history, figsize=figsize)
```



Baseline Evaluation

...And let's check the results

```
In [9]: tr_pred = nn.predict(tr[attributes])
        r2_tr = r2_score(tr[target], tr_pred)
        mae_tr = mean_absolute_error(tr[target], tr_pred)
        ts_pred = nn.predict(ts[attributes])
        r2_ts = r2_score(ts[target], ts_pred)
        mae_ts = mean_absolute_error(ts[target], ts_pred)
        print(f'R2 score: {r2_tr:.2f} (training), {r2_ts:.2f} (test)')
        print(f'MAE: {mae_tr:.2f} (training), {mae_ts:.2f} (test)')

        R2 score: 0.63 (training), 0.60 (test)
        MAE: 0.05 (training), 0.06 (test)
```

- They are not super (definitely not PreCrime level), but not alwful either
- Some improvements (not much) can be obtained with a Deeper model

We will keep Linear Regression as a baseline

- As a side benefit, we get to use an interpretable model!
- In particular, we can have evaluate the importance of each input attribute

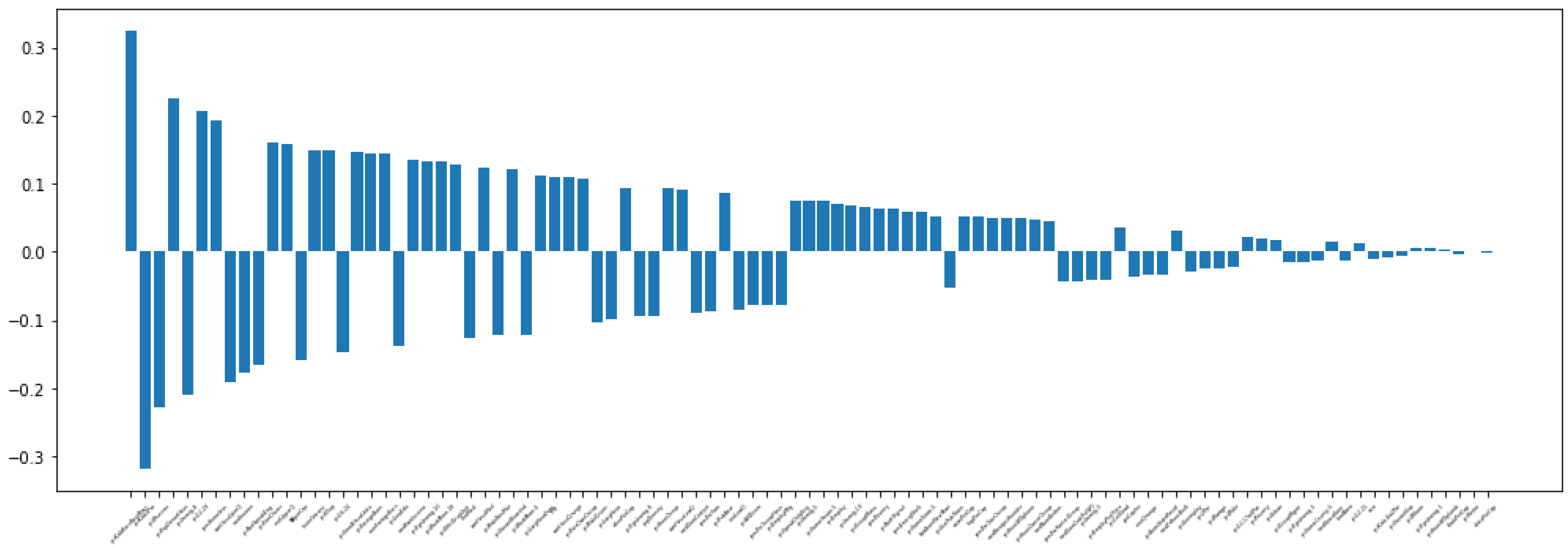
Important Attributes in Linear Regression

Important Attributes in Linear Regression

In particular, we can plot the weights by decreasing (absolute) value

- If all attributes are standardized/normalized (so they have similar ranges)
- ...Then the larger then (absolute) weight, the larger the impact

In [11]:
```
lr_weights = nn.get_weights()[0].ravel()
cst.plot_lr_weights(lr_weights, attributes, figsize=figsize)
```



Lasso

We can fix this by adding an L1 regularizer to obtain LASSO (Regression)

The regularizer penalizes large and small weights with a fixed rate

- Attributes for which the loss reduction does not match the regularization rate...
- ...Will be kept at zero, resulting in a sparse weight vector

Lasso is available in scikit-learn, and can be implemented in Keras/Tensorflow

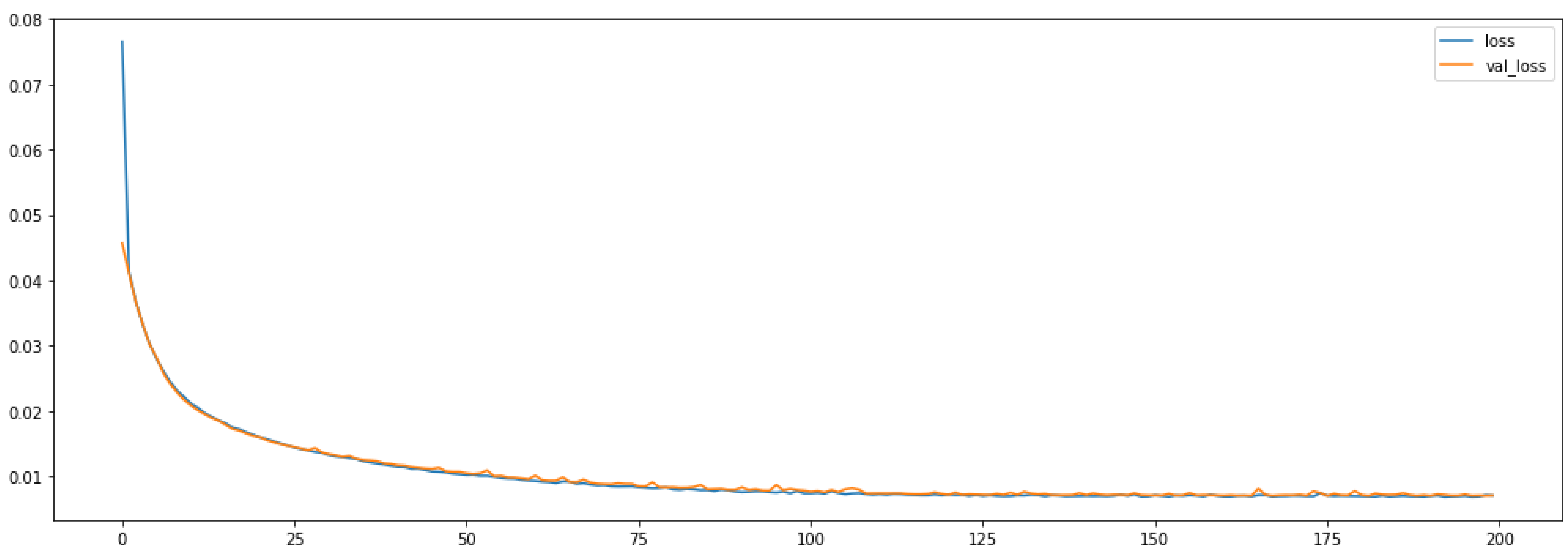
```
In [16]: nn2_in = layers.Input(len(attributes))
         nn2_out = layers.Dense(1, activation='linear', kernel_regularizer=regularizers.l1(l1=1e-3))(nn2_
         nn2 = keras.Model(nn2_in, nn2_out)
```

- We obtain it from Linear Regression by introducing an L1 weight regularizer

Lasso

We can train the Lasso model as usual

In [17]:
```
nn2.compile(optimizer='Adam', loss='mse')
cb2 = [callbacks.EarlyStopping(patience=20, restore_best_weights=True)]
history2 = nn2.fit(tr[attributes], tr[target], batch_size=32, epochs=200, verbose=0,
                   validation_split=0.2, callbacks=cb2)
cst.plot_training_history(history2, figsize=figsize)
```



Lasso Evaluation

The results are on par with Linear Regression

```
In [18]: tr_pred2 = nn2.predict(tr[attributes])
         r2_tr2 = r2_score(tr[target], tr_pred2)
         mae_tr2 = mean_absolute_error(tr[target], tr_pred2)

         ts_pred2 = nn2.predict(ts[attributes])
         r2_ts2 = r2_score(ts[target], ts_pred2)
         mae_ts2 = mean_absolute_error(ts[target], ts_pred2)

         print(f'R2 score: {r2_tr2:.2f} (training), {r2_ts2:.2f} (test)')
         print(f'MAE: {mae_tr2:.2f} (training), {mae_ts2:.2f} (test)')

         R2 score: 0.62 (training), 0.59 (test)
         MAE: 0.05 (training), 0.06 (test)
```

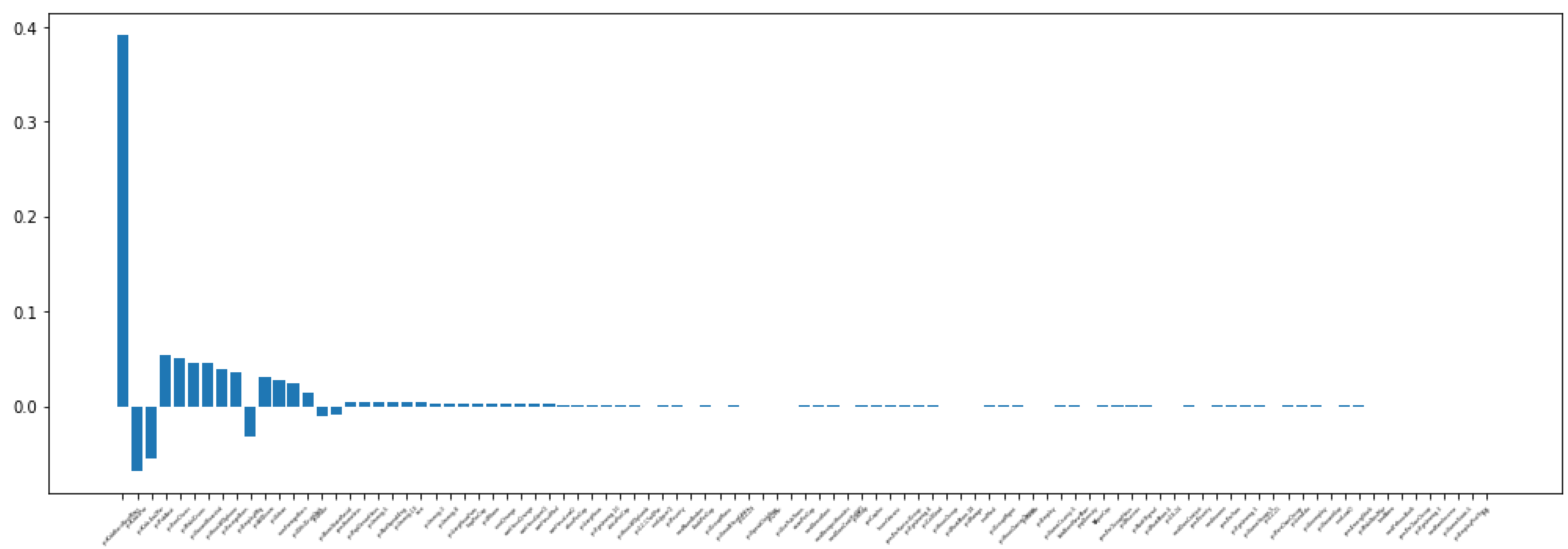
- The L1 term actually acts also as a traditional regularizer...
- ...And may therefore help to prevent overfitting

Important Attributes in Lasso

The main difference between LR and Lasso is int the weight vector

Lasso weights are sparse, i.e. only a few attributes will have a significant impact

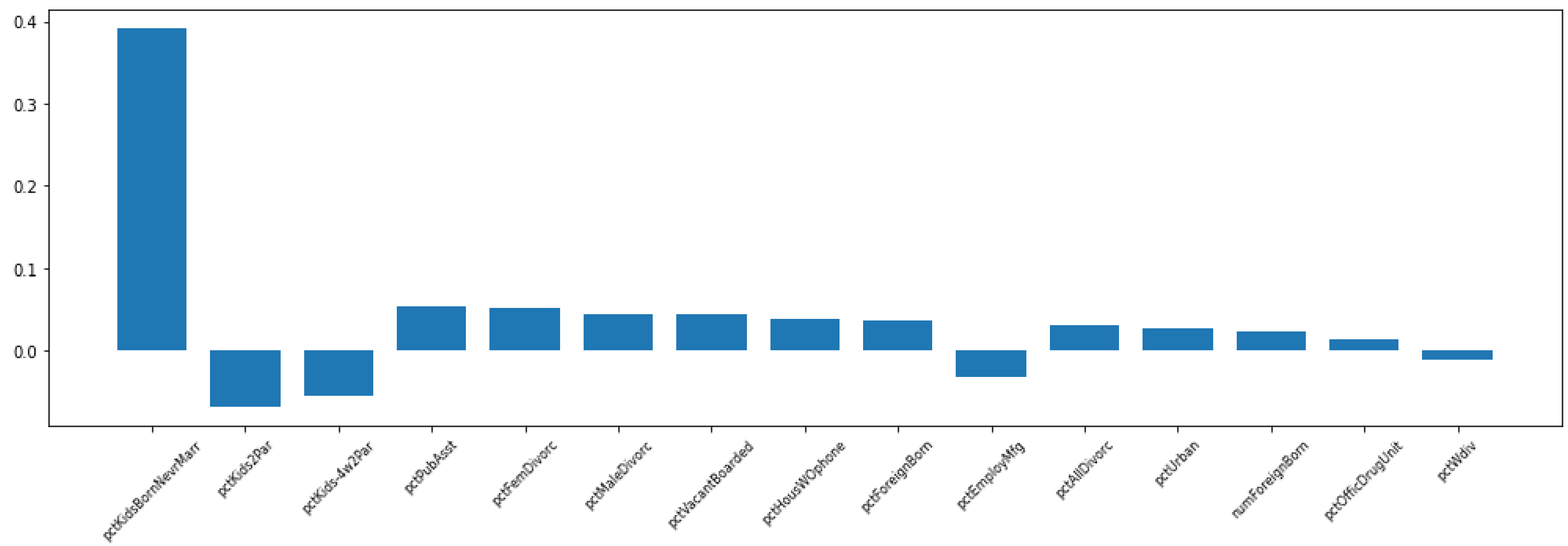
In [20]:
```
lasso_weights = nn2.get_weights()[0].ravel()
cst.plot_lr_weights(lasso_weights, attributes, figsize=figsize)
```



Important Attributes in Lasso

Let's zoom in on the 15 most important attributes

In [24]:
```
lasso_weights = nn2.get_weights()[0].ravel()
cst.plot_lr_weights(lasso_weights, attributes, cap_num=15, figsize=figsize)
```



The attribute "race" is nowhere to be seen!

Fairness Constraints

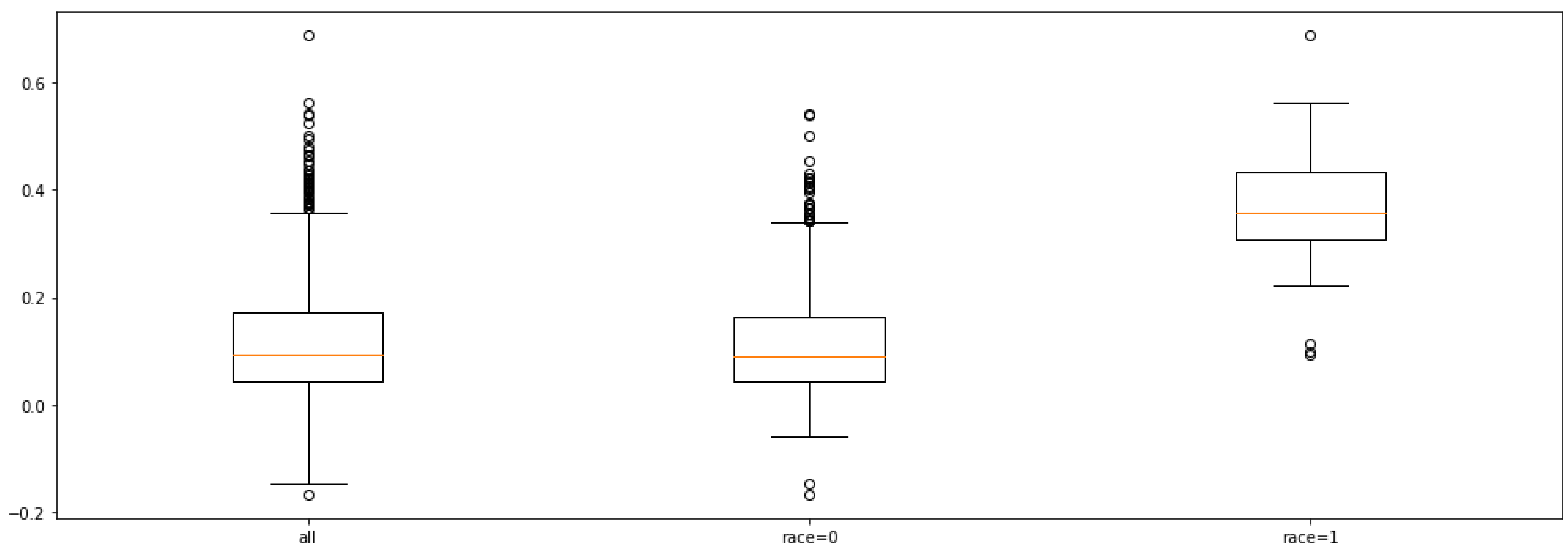
Discrimination Indexes

Discrimination can be linked to disparate treatment

- "Race" may not be even among the input attributes!
- ...Since it may be taken into account implicitly (i.e. via correlates)

Indeed, our model treats differently different groups:

In [28]:
```
cst.plot_pred_by_protected(tr, tr_pred, protected={'race': (0, 1)}, figsize=figsize)
```



Discrimination Indexes

A number of discrimination indexes attempt to measure discrimination

- This is open research area: there is no clear best choice
- Whether ethics itself can be measured is highly debatable!

Even if imperfect, this currently the best we can do

Classification and regression tasks usually call for different indexes

Here's an example from a recent AAAI paper

- Given a set of categorical protected attribute (indexes) J_p
- ...The regression form of the Disparate Impact Discrimination Index is given by:

$$\text{DIDI}_r = \sum_{j \in J_p} \sum_{v \in D_j} \left| \frac{1}{m} \sum_{i=1}^{m} y_i - \frac{1}{|I_{j,v}|} \sum_{i \in I_{j,v}} y_i \right|$$

DIDI

Let's make some intuitive sense of the DIDI_r formula

$$\sum_{j \in J_p} \sum_{v \in D_j} \left| \frac{1}{m} \sum_{i=1}^{m} y_i - \frac{1}{|I_{j,v}|} \sum_{i \in I_{j,v}} y_i \right|$$

- $\frac{1}{m} \sum_{i=1}^{m} y_i$ is just the average predicted value
- ...For examples where the protected attribute takes specific values
- $\frac{1}{|I_{j,v}|} \sum_{i \in I_{j,v}} y_i$ is the average prediction for a social group

We penalize the group predictions for deviating from the global average

- Obviously this is not necessarily the best definition, but it is something
- In general, different tasks will call for different discrimination indexes

...And don't forget the whole "can we actually measure ethics" issue ;-)

DIDI

We can compute the DIDI via the following function

```
def DIDI_r(data, pred, protected):
    res, avg = 0, np.mean(pred)
    for aname, dom in protected.items():
        for val in dom:
            mask = (data[aname] == val)
            res += abs(avg - np.mean(pred[mask]))
    return res
```

- `protected` contains the protected attribute names with their domain

For our original Linear Regression model, we get

```
In [29]: tr_DIDI = cst.DIDI_r(tr, tr_pred, protected)
         ts_DIDI = cst.DIDI_r(ts, ts_pred, protected)
         print(f'DIDI: {tr_DIDI:.2f} (training), {ts_DIDI:.2f} (test)')

         DIDI: 0.25 (training), 0.27 (test)
```

Fairness Constraints

Discrimination indexes can be used to state fairness constraints

For example, we may require:

$$\text{DIDI}_r(y) \leq \theta$$

If the chosen index is differentiable...

...Then we may try to inject the constraint via a semantic regularizer

- For example, we may use a loss function in the form:

$$L(y, \hat{y}) + \lambda \max(0, \text{DIDI}_r(y) - \theta)$$

For non-differentiable indexes (e.g. those found in classification), we can:

- Use a differentiable approximation (with some care!)
- Use an approach that does not require differentiability, e.g. this or that

Fairness as a Semantic Regularizer

We can once again use a custom Keras model

```
class CstDIDIRegressor(MLPRegressor):
    def __init__(self, attributes, protected, alpha, thr, hidden=[]): ...

    def train_step(self, data): ...

    @property
    def metrics(self): ...
```

The full code can be found in the support module

- We subclass our `MLPRegressor` (itself a subclass of `keras.Model`)
- ...And we provide a custom training step
- `alpha` is the regularizer weight
- `thr` is the DIDI threshold

In this case, we do not need a custom batch generator

Fairness as a Semantic Regularizer

The main logic is in the first half of the `train_step` method:

```
def train_step(self, data):
    x, y_true = data # unpacking the mini-batch
    with tf.GradientTape() as tape:
        y_pred = self(x, training=True) # obtain predictions
        mse = self.compiled_loss(y_true, y_pred) # base loss (kept external)
        ymean = k.mean(y_pred) # avg prediction
        didi = 0 # DIDI computation
        for aidx, dom in self.protected.items():
            for val in dom:
                mask = (x[:, aidx] == val)
                didi += k.abs(ymean - k.mean(y_pred[mask]))
        cst = k.maximum(0.0, didi - self.thr) # Regularizer
        loss = mse + self.alpha * cst
```

- In this case we chose to let the main loss be defined externally
- ...Which means we will need to define it when calling `compile`

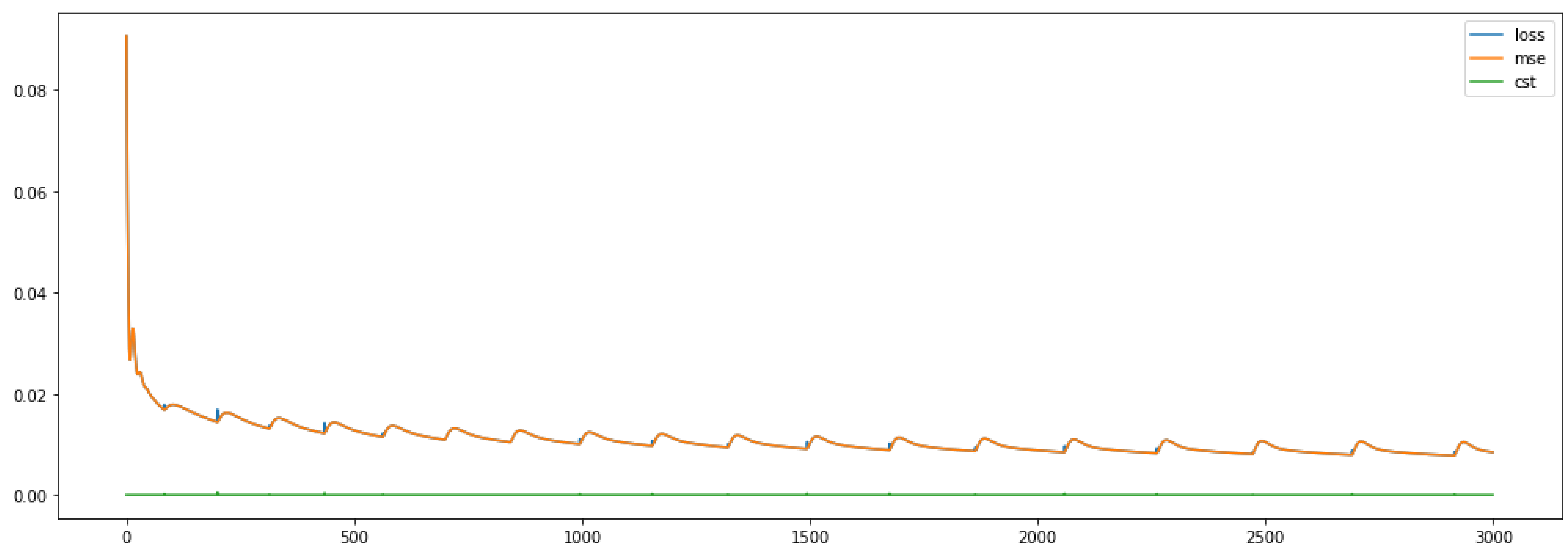
Training the Constrained Model

Let's try and train the model, trying to roughly halve the DIDI

Important: it will be a good idea to need to keep all examples in every batch

- Using mini-batches makes constraint satisfaction (more) stochastic

In [31]:
```
didi_thr = 0.13
nn3 = cst.CstDIDIRegressor(attributes, protected, alpha=5, thr=didi_thr, hidden=[])
nn3.compile(optimizer='Adam', loss='mse')
history3 = nn3.fit(tr[attributes], tr[target], batch_size=len(tr), epochs=3000, verbose=0)
cst.plot_training_history(history3, figsize=figsize)
```



Constrained Model Evaluation

Let's check both the prediction quality and the DIDI

```
In [32]: tr_pred3 = nn3.predict(tr[attributes])
r2_tr3 = r2_score(tr[target], tr_pred3)
mae_tr3 = mean_absolute_error(tr[target], tr_pred3)

ts_pred3 = nn3.predict(ts[attributes])
r2_ts3 = r2_score(ts[target], ts_pred3)
mae_ts3 = mean_absolute_error(ts[target], ts_pred3)

tr_DIDI3 = cst.DIDI_r(tr, tr_pred3, protected)
ts_DIDI3 = cst.DIDI_r(ts, ts_pred3, protected)

print(f'R2 score: {r2_tr3:.2f} (training), {r2_ts3:.2f} (test)')
print(f'MAE: {mae_tr3:.2f} (training), {mae_ts3:.2f} (test)')
print(f'DIDI: {tr_DIDI3:.2f} (training), {ts_DIDI3:.2f} (test)')
```

```
R2 score: 0.45 (training), 0.39 (test)
MAE: 0.06 (training), 0.07 (test)
DIDI: 0.09 (training), 0.09 (test)
```

- It seems we have overdone it: the constraint is satisfied with some slack
- ...And that came at the price of a strongly reduced predictive performance

Lagrangian Dual Framework

Choosing the Right Weight

Choosing the regularizer weight in our setup is particularly tricky

- Unlike in our RUL case study, we are not using domain knowledge...
- ...To enhance the prediction quality of the regressor

So, we cannot optimize some accuracy score on a separate validation set

In fact, the fairness constraint and accuracy are conflicting goals

- Satisfying the constraint has in this case higher priority
- So in principle we could resort to a lexicographic objective...
- ...But that kind of approach is prone to numerical issues

A simpler, recent approach consists in relying on Lagrangian duality

Lagrangian Duality for Constrained ML

Let's consider our semantic regularized loss

$$\mathcal{L}(y, \lambda) = L(y, \hat{y}) + \lambda \max\left(0, \mathrm{DIDI}_r(y) - \theta\right)$$

It can be generalized to:

$$\mathcal{L}(y, \lambda) = L(y, \hat{y}) + \lambda \max\left(0, g(y)\right)$$

- Where $g(y)$ is some kind of constraint function

This is actually related to the constrained problem we really care about:

$$\min\{L(y, \hat{y}) \mid g(y) \leq 0\}$$

To be precise, the formulation is a Lagrangian relaxation

Lagrangian Duality for Constrained ML

Our regularized loss $\mathcal{L}(y, \lambda)$ is actually called a Lagrangian

Specifically, the form somerimes in the penalty method

$$\mathcal{L}(y, \lambda) = L(y, \hat{y}) + \lambda \max(0, g(y))$$

Let's consider its relation with the original constrained formulation:

- Whenever the constraint is satisfied, we have that $\mathcal{L}(y, \lambda) = L(h, \hat{y})$
- ...No matter what what value λ takes
- When the constraint is not satisfied, $\mathcal{L}(y, \lambda)$ will be higher than $L(y, \hat{y})$

This means that, for any given λ, we have that:

$$\min_y \mathcal{L}(y, \lambda) \leq \min\{L(y, \hat{y}) \mid g(y) \leq 0\}$$

I.e. the relaxation optimum cannot be larger then the constrained optimum

Lagrangian Duality for Constrained ML

So, for any λ, solving:

$$\min_y \mathcal{L}(y, \lambda)$$

...Gives a lower bound on the optimum of the constrained problem

So, among many lower bounds why not taking the largest one?

Formally, this means solving:

$$\max_\lambda \left(\min_y \mathcal{L}(y, \lambda) \right)$$

Intuitively:

- We choose y to minimize the Lagrangian (the "regularized loss")
- We choose λ to maximize the Lagrangian

This latter problem is known as Lagrangian dual

Lagrangian Duality for Constrained ML

This Lagrangian dual approach can be extremely powerful

- It gives us a criterion for choosing λ
- It can be (approximately) implemented without an outer search loop:
  - We can make one gradient step over y to minimize $\mathcal{L}$
  - ...Then a second gradient step over λ to maximize $\mathcal{L}$
- It is not limited to fairness constraints
  - It works for any differentiable constraint function
  - ...And even when there are many constraints with distinct weights
  - ...Which BTW in this context are called "multipliers"
- If the penalty terms is well chosen, the method has convergence guarantees
  - However, these are limited to fully convex setups
  - I.e. convex loss, model, and constraint function (like our case study!)
  - In practice, it is however often used as a heuristic

Implementing the Lagrangian Dual Approach

We will implement the Lagrangian dual approach via another custom model

```
class LagDualDIDIRegressor(MLPRegressor):
    def __init__(self, attributes, protected, thr, hidden=[]):
        super(LagDualDIDIRegressor, self).__init__(len(attributes), hidden)
        self.alpha = tf.Variable(0., name='alpha')
        ...

    def __custom_loss(self, x, y_true, sign=1): ...

    def train_step(self, data): ...

    def metrics(self): ...
```

- We no longer pass a fixed `alpha` weight/multiplier
- Instead we use a trainable variable

Implementing the Lagrangian Dual Approach

In the `__custom_loss` method we compute the Lagrangian/regularized loss

```
def __custom_loss(self, x, y_true, sign=1):
    y_pred = self(x, training=True) # obtain the predictions
    mse = self.compiled_loss(y_true, y_pred) # main loss
    ymean = k.mean(y_pred) # average prediction
    didi = 0 # DIDI computation
    for aidx, dom in self.protected.items():
        for val in dom:
            mask = (x[:, aidx] == val)
            didi += k.abs(ymean - k.mean(y_pred[mask]))
    cst = k.maximum(0.0, didi - self.thr) # regularizer
    loss = mse + self.alpha * cst
    return sign*loss, mse, cst
```

- The code is the same as before
- ...Except that we can flip the loss sign via a function argument (i.e. `sign`)

Implementing the Lagrangian Dual Approach

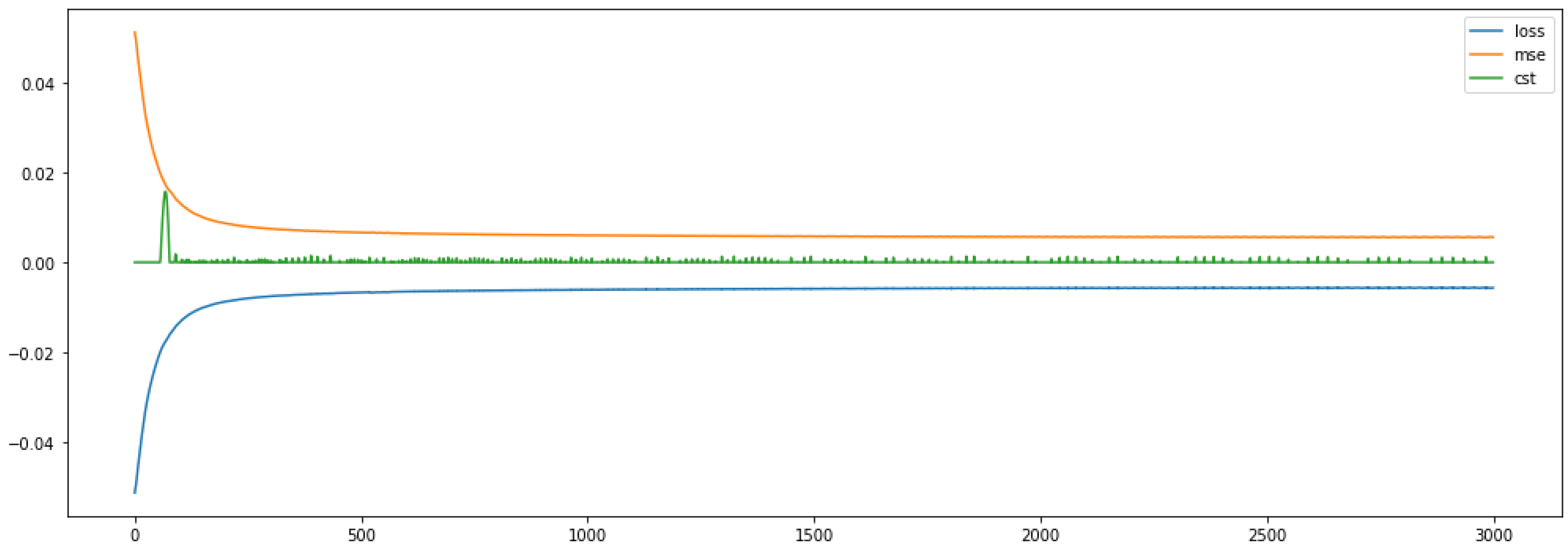
In the training method, we make two distinct gradient steps:

```
def train_step(self, data):
    x, y_true = data # unpacking
    with tf.GradientTape() as tape: # first loss (minimization)
        loss, mse, cst = self.__custom_loss(x, y_true, sign=1)
    # Separate training variables
    tr_vars = self.trainable_variables
    wgt_vars = tr_vars[:-1] # network weights
    mul_vars = tr_vars[-1:] # multiplier
    grads = tape.gradient(loss, wgt_vars) # adjust the network weights
    self.optimizer.apply_gradients(zip(grads, wgt_vars))
    with tf.GradientTape() as tape: # second loss (maximization)
        loss, mse, cst = self.__custom_loss(x, y_true, sign=-1)
    grads = tape.gradient(loss, mul_vars) # adjust lambda
    self.optimizer.apply_gradients(zip(grads, mul_vars))
```

Training the Lagrangian Dual Approach

In [34]:
```
nn4 = cst.LagDualDIDIRegressor(attributes, protected, thr=didi_thr, hidden=[])
nn4.compile(optimizer='Adam', loss='mse')
history4 = nn4.fit(tr[attributes], tr[target], batch_size=len(tr), epochs=3000, verbose=0)

cst.plot_training_history(history4, figsize=figsize)
```



Lagrangian Dual Evaluation

Let's check the new results

In [35]:

```
tr_pred4 = nn4.predict(tr[attributes])
r2_tr4 = r2_score(tr[target], tr_pred4)
mae_tr4 = mean_absolute_error(tr[target], tr_pred4)

ts_pred4 = nn4.predict(ts[attributes])
r2_ts4 = r2_score(ts[target], ts_pred4)
mae_ts4 = mean_absolute_error(ts[target], ts_pred4)

print(f'R2 score: {r2_tr4:.2f} (training), {r2_ts4:.2f} (test)')
print(f'MAE: {mae_tr4:.2f} (training), {mae_ts4:.2f} (test)')

tr_DIDI4 = cst.DIDI_r(tr, tr_pred4, protected)
ts_DIDI4 = cst.DIDI_r(ts, ts_pred4, protected)
print(f'DIDI: {tr_DIDI4:.2f} (training), {ts_DIDI4:.2f} (test)')
```

```
R2 score: 0.63 (training), 0.56 (test)
MAE: 0.05 (training), 0.06 (test)
DIDI: 0.12 (training), 0.13 (test)
```

- The DIDI has the desired value (on the test set, this is only roughly true)
- ...And the prediction quality is much higher (close to the original value)

Final Considerations

The idea of injecting constraints in ML is attracting research interest

- It can be used to take advantage of domain/symbolic knowledge
- It can be used to improve reliability and fairness

We haven't covered all possible approaches

- E.g. it is possible to incorporate constraints in the model structure
- ...Or using constraints to correct the model output
- A recent buzzword to watch for: neuro-symbolic integration

It is still an active research topic, with many open issues

- E.g. how to deal with non-differentiable constraints (project works available)
- E.g. how to deal with large scale relational constraints (such as fairness ones)
- E.g. how to tune/learn constraint multipliers for soft constraint
- ...