Лабораторная работа №1.
Обучение нейросетевых регрессора и классификаторов. Вариант 2.
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Группа: 932003

1. Описание наборов данных.

Существует три основных набора данных, использованных в данной работе:

1. Общий набор данных для банка, который содержит информацию об клиентах банка. Это включает такие данные, как возраст, профессия, образование, семейное положение, наличие кредита и другие.

bank-additional-full.csv - размеченный набор данных для бинарной классификации. Данные связаны с прямыми маркетинговыми кампаниями португальского банковского учреждения. Цель бинарной классификации состоит в том, чтобы предсказать, подпишется ли клиент на срочный банковский депозит (переменная у)

2. Набор данных о здоровье плода, который содержит данные по различным показателям, связанным со здоровьем плода в период беременности.

fetal_health.csv - набор данных для многоклассовой классификации. Данный набор данных составлен из результатов кардиотокографии. Для этого мы создаем многоклассовую модель, чтобы классифицировать функции КТГ по трем состояниям здоровья плода: нормальное (1), подозрительное (2) и паталогическое (3).

3. Набор данных об энергетическом потреблении, который содержит информацию о потреблении энергии в разных областях.

DS_2019_public.csv - набор данных для регрессии. Данный набор данных содержит информацию о потреблении энергии в зданиях. В этом наборе данных мы будем классифицировать по TOTALBTUCOL - общее потребление энергии для кондиционирования воздуха, в тысячах BTU. BTU - Британская тепловая единица.

2. Признаки, которые были использованы для анализа.

Признаки, используемые для анализа, преобразовывались и масштабировались в процессе предварительной обработки данных. В этом процессе категориальные признаки были преобразованы в числовые, а все признаки были приведены к одному масштабу.

В пункте А:

Признаки, использованные для анализа:

1. marital (семейное положение) был перекодирован в Marital Binary, где женатые/замужем получают 1, а все остальные получают 0.

- 2. default (есть ли у субъекта непогашенные кредиты) был перекодирован в Default Binary, где заемщики с кредитами в просрочке получают 1, а все остальные получают 0.
- 3. housing (имеет ли субъект ипотеку) был перекодирован в Housing Binary, где те, кто имеет ипотеку, получают 1, а все остальные получают 0.
- 4. loan (есть ли у субъекта личные заемные средства) был перекодирован в Loan Binary, где те, у кого есть личные заемные средства, получают 1, а все остальные получают 0.
- 5. poutcome (результат прошлой маркетинговой кампании) был перекодирован в Poutcome Binary, где успешные результаты получают 2, несуществующие получают 1, а все другие получают 0.
- 6. И остальные признаки которые не требовали перекодировки:

Следующие признаки были исключены из анализа:

- 1. у Исключен, поскольку этот столбец был перекодирован в Target Binary и использовался в качестве целевого столбца для нашей задачи классификации.
- 2. job Работа клиента, исключен, это связано с тем, что этот столбец является номинальным и требует дополнительной предварительной обработки, чтобы быть полезным для модели.
- 3. education Образование клиента. Исключено теми же причинами, что и job.
- 4. contact Способ связи с клиентом исключен по той же причине, что и job и education.
- 5. month, day_of_week Месяц и день недели последнего контакта. Исключены из-за незначительного влияния на вероятность подписания депозита.

В пункте В:

Были использованы все признаки, кроме fetal_health, поскольку этот столбец был перекодирован в Target Multi и использовался в качестве целевого столбца для нашей задачи классификации. Эти данные представляют особенности здоровья плода, полученные на основе кардиографии плода

```
Data columns (total 22 columns):
                                                                             Non-Null Count Dtype
# Column
     -----
                                                                             -----
0 baseline value
                                                                             2126 non-null float64
                                                                            2126 non-null float64
2126 non-null float64
2126 non-null float64
2126 non-null float64
2126 non-null float64
2126 non-null float64
2126 non-null float64
2126 non-null float64
2126 non-null float64
2126 non-null float64
    accelerations
    fetal movement
    uterine_contractions
light_decelerations
     severe decelerations
    prolongued_decelerations
abnormal_short_term_variability
8 mean_value_of_short_term_variability
9 percentage_of_time_with_abnormal_long_term_variability 2126 non-null float64
10 mean_value_of_long_term_variability 2126 non-null float64
                                                                             2126 non-null float64
11 histogram width
                                                                             2126 non-null float64
12 histogram_min
                                                                             2126 non-null float64
13 histogram max
                                                                             2126 non-null float64
14 histogram number of peaks
                                                                             2126 non-null float64
15 histogram_number_of_zeroes
                                                                             2126 non-null float64
16 histogram mode
                                                                             2126 non-null float64
17 histogram mean
                                                                             2126 non-null float64
18 histogram_median
                                                                             2126 non-null float64
19 histogram_variance
                                                                             2126 non-null float64
 20 histogram_tendency
21 fetal_health
                                                                             2126 non-null float64
dtypes: float64(22)
```

В пункте С:

Для анализа использовались все столбцы набора данных "DS_2019_public.csv", кроме 'TOTALBTUCOL'. Этот столбец был выделен как целевая переменная (у), которую необходимо было предсказать, в то время как все остальные столбцы были использованы как признаки (X) для модели.

Остальные данные были предварительно обработаны (были удалены строки с некорректными значениями), затем прошли масштабирование при помощи MinMaxScaler (все признаки были приведены к диапазону между 0 и 1).

```
df.columns
Index(['Climate_Region_Pub', 'DIVISION', 'REPORTABLE_DOMAIN', 'DOLELCOL',
        'TOTALDOLCOL', 'KWHCOL', 'BTUELCOL', 'TOTALBTUCOL', 'TOTALDOLSPH'
        'TOTALBTUSPH',
        'LGT1EE', 'TOTALBTUWTH', 'ROOFTYPE', 'DOLELRFG', 'TOTALDOLRFG', 'HEATROOM', 'WDWATER', 'UGWARM', 'DRYRFUEL', 'KWHRFG'],
      dtype='object', length=121)
df.dtypes
Climate_Region_Pub
                          int64
DIVISION
                          int64
REPORTABLE DOMAIN
                          int64
DOLELCOL
                          object
TOTALDOLCOL
                          int64
                           int64
HEATROOM
                           int64
WDWATER
                           int64
UGWARM
DRYRFUEL
                           int64
                        float64
KWHRFG
Length: 121, dtype: object
```

3. Параметры архитектур и обучения нейронных сетей, использованные для обучения.

Построены три различные модели: для бинарной классификации, многоклассовой классификации и регрессии.

Для каждой из них были использованы полносвязные нейронные сети. В модели бинарной классификации на последнем слое использовалась сигмоидная функция активации, в многоклассовой классификации - softmax, а в модели регрессии - линейная функция активации. Количество нейронов в скрытых слоях варьировалось в зависимости от модели.

A)

Архитектура сети: Сеть является бинарным классификатором и составлена из последовательности слоев (Sequential). Сначала добавляется Dense слой, который имеет 4 нейрона, с функцией активации ReLU, и принимающий на вход данные с 15 признаками. Затем следует еще один Dense слой с одним нейроном и функцией активации 'sigmoid', предназначенный для предоставления выходного значения.

Компиляция модели: Функция потерь, использованная в этой модели, - это бинарная кросс-энтропия, которая часто используется для задач бинарной классификации. Оптимизатор 'Adam' использовался для настройки весов модели. Метрика, используемая для оценки производительности модели в процессе обучения, - это точность(ассигасу).

Обучение модели: Модель была обучена в течение 25 эпох, с размером пакета 10. Был использована валидационная выборка и коллбеки для ранней остановки и сохранения лучших весов модели. Режим валидации был поставлен на 'max' и показатель для проверки - 'val_accuracy'. Остановка обучения осуществляется, если нет улучшений в показателе 'val_accuracy' в течение 15 эпох.

B)

Архитектура сети: Аналогично предыдущему примеру, эта сеть создана с использованием модели последовательных слоев в Keras. Она также содержит два плотных слоя. Первый плотный слой имеет 8 нейронов с функцией активации ReLU. Второй - 4 нейрона с функцией активации "softmax". Функция активации "softmax" используется в задачах многоклассовой классификации, так как она предоставляет вероятностные оценки, которые суммируются в 1.

Компиляция модели: Сеть компилируется с функцией потерь "categorical_crossentropy", которая используется в задачах многоклассовой классификации. В качестве оптимизатора используется 'adam'. Метрика, используемая для оценки производительности модели, - 'accuracy'.

Обучение модели: Модель обучается в течение 50 эпох с размером пакета 20. Используются валидационные данные, а также коллбеки для ранней остановки и сохранения лучших весов модели. Показателем валидации является 'val_accuracy'. Мониторинг прекращается, если нет улучшения указанного показателя в течение 15 эпох.

C)

Архитектура нейронной сети: Создается последовательная модель в Keras, состоящающая из трех полносвязных слоев. Первый слой содержит 120 нейронов с функцией активации ReLU, второй слой состоит из 60 нейронов с функцией активации ReLU и на выходе один слой с линейной активацией. Функция активации ReLU используется для предотвращения проблемы затухания градиента, а линейная активация выбирается для задачи регрессии.

Компиляция модели: Модель компилируется с функцией потерь MSE (среднеквадратичная ошибка), использующуюся для задач регрессии, и оптимизатором Adam. Также отслеживается метрика MAE (средняя абсолютная ошибка).

Обучение модели: Модель обучается в течение 350 эпох с размером пакета 40. Добавляются функции обратного вызова для ранней остановки

обучения, если модель перестает улучшаться (с терпением в 20 эпох), и сохранения лучших весов модели. Валидационные данные используются в процессе обучения для оценки производительности модели на данных, которые она не видела.

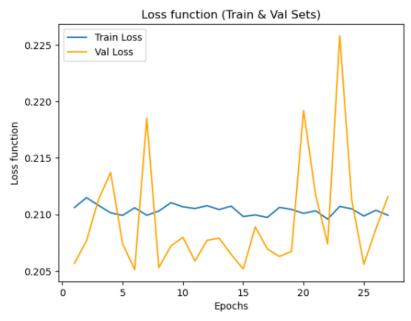
4. Графики обучения для архитектур нейронных сетей с лучшими характеристиками эффективности

Графики обучения, представленные в коде, показывают как потери, так и точность модели в процессе обучения для тренировочного и валидационного набора данных.

A)

```
loss_function = binary_classifier_history.history['loss']
val_loss_function = binary_classifier_history.history['val_loss']
epochs = range(1,len(loss_function)+1)

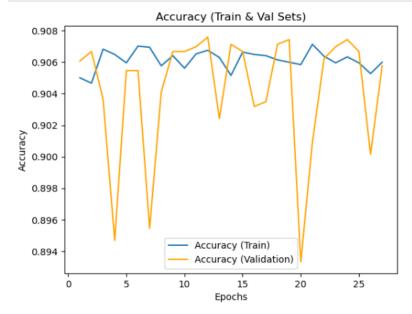
plt.title('Loss function (Train & Val Sets)')
plt.plot(epochs,loss_function,label='Train Loss')
plt.plot(epochs,val_loss_function,color='orange',label='Val Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss function')
plt.legend()
plt.show()
```



Построение графика точности в процессе обучения

```
]: acc = binary_classifier_history.history['accuracy']
val_acc = binary_classifier_history.history['val_accuracy']
epochs = range(1,len(acc)+1)

plt.title('Accuracy (Train & Val Sets)')
plt.plot(epochs,acc,label='Accuracy (Train)')
plt.plot(epochs,val_acc,color='orange',label='Accuracy (Validation)')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

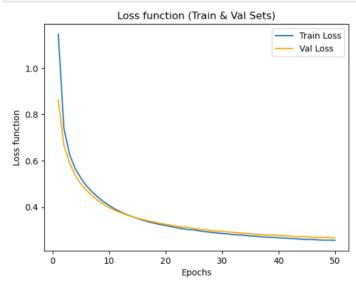


B)

Построение графика потери

```
BBOQ [38]: loss_function = multi_classifier_history.history['loss']
val_loss_function = multi_classifier_history.history['val_loss']
epochs = range(1,len(loss_function)+1)

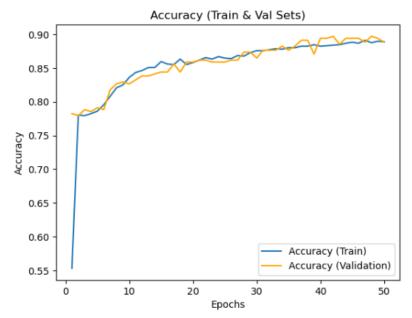
plt.title('Loss function (Train & Val Sets)')
plt.plot(epochs,loss_function,label='Train Loss')
plt.plot(epochs,val_loss_function,color='orange',label='Val Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss function')
plt.legend()
plt.show()
```



Построение графика точности

```
acc = multi_classifier_history.history['accuracy']
val_acc = multi_classifier_history.history['val_accuracy']
epochs = range(1,len(acc)+1)

plt.title('Accuracy (Train & Val Sets)')
plt.plot(epochs,acc,label='Accuracy (Train)')
plt.plot(epochs,val_acc,color='orange',label='Accuracy (Validation)')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



C)

Построение графика потери

Если функция потерь на тренировочной выборке продолжает уменьшаться, в то время как на валидационной выборке начинает возрастать, это является признаком переобучения

```
[31]: loss_function = regressor_history.history['loss']
    val_loss_function = regressor_history.history['val_loss']
    epochs = range(1, len(loss_function)+1)

plt.title('Loss function (Train & Val Sets)')
    plt.plot(epochs, loss_function, label='Train Loss')
    plt.plot(epochs, val_loss_function, color='orange', label='Val Loss')
    plt.ylabel('Epochs')
    plt.ylabel('Loss function')
    plt.legend()
    plt.show()
```

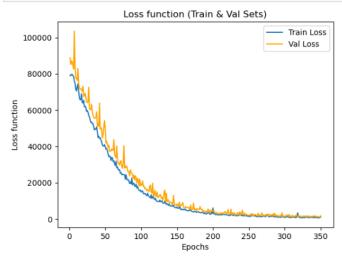
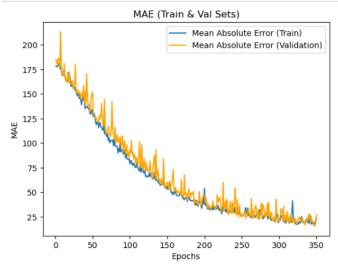


График изменения величины средней абсолютной ошибки (Mean Absolute Error, MAE) модели в процессе

Две кривые: одна для обучающего набора данных ("Mean Absolute Error (Train)") и для валидационного набора данных ("Mean Absolute Error (Validation)"). Если на графике видно, что ошибка на обучающей выборке продолжает уменьшаться, в то время как ошибка на валидационной выборке начинает увеличиваться, это может свидетельствовать о переобучении модели, когда она хорошо обучается на тренировочных данных, но плохо справляется с новыми, наблюдаемыми во время валидации данными.

```
mae = regressor_history.history['mae']
val_mae = regressor_history.history['val_mae']
epochs = range(1, len(mae)+1)

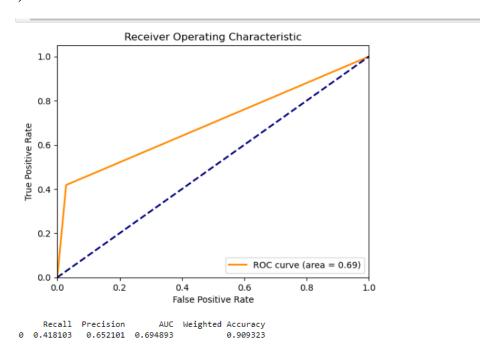
plt.title('MAE (Train & Val Sets)')
plt.plot(epochs, mae, label='Mean Absolute Error (Train)')
plt.plot(epochs, val_mae, color='orange', label='Mean Absolute Error (Validation)')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.legend()
plt.show()
```

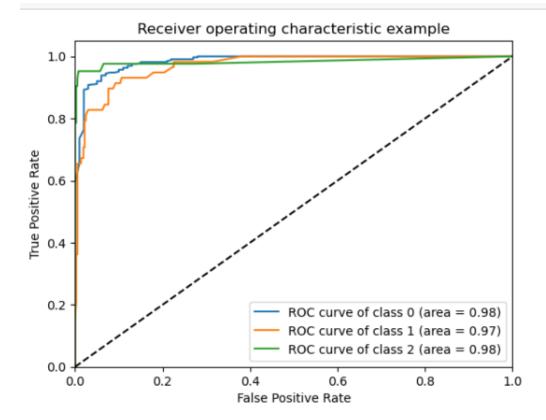


5. ROC-кривые классов для лучших классификаторов.

ROC-кривые, представленные в коде, дают визуализацию того, как хорошо наши бинарные и многоклассовые классификаторы справляются с обобщением на новые данные.







6. Оценки моделей на тестовых выборках в виде таблиц/ диаграмм, отображающих метрики качества.

Оценки моделей, показанные в коде, включают такие метрики, как точность, полноту, MAE, MSE и коэффициент детерминации (R2).

Все указанные оценки были произведены на разделенных тестовых выборках, чтобы обеспечить корректное измерение эффективности модели. Графики позволяют визуально анализировать процесс обучения машины, а таблицы и диаграммы предоставляют числовые оценки метрик качества моделей.

Дополнительно вы можете обратить внимание на использование EarlyStopping и ModelCheckpoint, это обеспечивает сохранение лучшей модели и прекращение обучения в случае, если результаты не улучшаются на протяжении фиксированного количества эпох.

A)

1. Recall (полнота) равен 0.418, что означает, что модель правильно классифицировала только 41.8% положительных результатов из всех

истинных положительных результатов. Recall важен, когда ложно отрицательные результаты являются недопустимыми, и мы хотим минимизировать их количество.

- 2. Precision (точность) составляет 0.652, что означает, что модель верно классифицировала 65.2% от всех предсказанных положительных результатов. Precision важна, когда ложно положительные результаты являются недопустимыми, и мы хотим минимизировать их количество.
- 3. AUC (площадь под ROC-кривой) равна 0.695. ROC-кривая показывает зависимость между чувствительностью (True Positive Rate) и специфичностью (1 False Positive Rate) модели при изменении порога классификации. AUC меряет общую производительность модели и должен быть максимально близким к 1.
- 4. Weighted Accuracy (взвешенная точность) составляет 0.909. Взвешенная точность учитывает дисбаланс классов в данных, присваивая вес каждому классу в зависимости от его доли в выборке.

Вывод: Модель имеет достаточно высокую точность и AUC, что может говорить о ее хорошей способности классифицировать данные. Однако полнота (recall) невысока, что означает, что модель может пропускать много истинно положительных результатов.

258/258 [========] - 1s

Recall: 0.41810344827586204 Precision: 0.6521008403361345

AUC: 0.6948930374074249

Weighted Accuracy: 0.9093226511289147

B)

- 1. Precision (точность): это метрика, показывающая, какая доля объектов, отнесённых моделью к классу 1, действительно относится к классу 1. Модель имеет точность 0.942, что свидетельствует о том, что почти 94.2% всех положительных предсказаний модели действительно верны.
- 2. Recall (полнота): это метрика, показывающая, какую часть объектов класса 1 из всех объектов класса 1 модель смогла обнаружить. Величина полноты в 0.9436 говорит о том, что модель идентифицировала почти 94.36% всех истинных положительных случаев.
- 3. AUC-ROC: AUC равен 0.979. Эта метрика говорит о том, насколько модель способна отличить положительные и отрицательные данные чем ближе значение к 1, тем лучше. 0.979 высокий показатель.

4. Weighted Accuracy также равно 0.944, что является высокой оценкой.

Вывод: Основываясь на этих данных, можно сказать, что мультиклассовый классификатор в рамках существующего набора данных работает отлично.

```
print("Weighted Accuracy: ", accuracy)

Precision: 0.9424434917086499

Recall: 0.9436619718309859

AUC: 0.9793782735877897

Weighted Accuracy: 0.9436619718309859
```

C)

- 1. MSE (Mean Squared Error, Средняя квадратическая ошибка) составляет 1588.58. MSE является общепризнанной мерой качества регрессионных предсказаний и чем меньше её значение, тем качественнее работает модель.
- 2. MAE (Mean Absolute Error, Средняя абсолютная ошибка) равна 28.06. Это абсолютное значение разности между реальными и прогнозными значениями. Чем меньше это число, тем лучше качество модели.
- 3. Коэффициент детерминации R² составляет почти 1 (0.99998), что является отличным значением и означает, что модель объясняет почти 100% вариации зависимой переменной.

Вывод: по представленным метрикам, модель показывает отличные результаты, причем коэффициент детерминации превосходно близок к 1.

MSE: 1588.583464797732 MAE: 28.06361318617011 R2: 0.9999828651563029

7. Программный код.

Лабораторная работа № 1

Боровских Вадим, 932003

A) Бинарный Классификатор bank-additional-full

```
import matplotlib.pyplot as plt
In [1]:
          import seaborn as sns
          import pandas as pd
          import numpy as np
          from sklearn.preprocessing import MinMaxScaler
          from sklearn.model_selection import train_test_split
          import matplotlib.pyplot as plt
          from keras.models import Sequential
          from keras.layers import Dense
          from keras.callbacks import ModelCheckpoint, EarlyStopping
In [2]:
          df = pd.read_csv("bank-additional-full.csv",sep=";", quotechar='"', index_col = 0)
          df=df.reset_index()
          df
Out[2]:
                                  marital
                                                  education
                                                               default housing
                                                                                        contact month d
                 age
                             job
              0
                  56
                      housemaid
                                  married
                                                    basic.4y
                                                                   no
                                                                            no
                                                                                  no
                                                                                      telephone
                                                                                                   may
                   57
                         services
                                  married
                                                 high.school unknown
                                                                                      telephone
                                                                            no
                                                                                                   may
                                                                                  no
              2
                   37
                                                 high.school
                         services married
                                                                   no
                                                                            yes
                                                                                  no
                                                                                      telephone
                                                                                                   may
                   40
                          admin. married
                                                    basic.6y
                                                                                      telephone
                                                                   no
                                                                            no
                                                                                  no
                                                                                                   may
              4
                   56
                                                 high.school
                         services married
                                                                   no
                                                                            no
                                                                                 yes
                                                                                      telephone
                                                                                                   may
          41183
                   73
                          retired
                                 married
                                          professional.course
                                                                            yes
                                                                                  no
                                                                                         cellular
                                                                                                    nov
          41184
                  46
                       blue-collar
                                  married
                                          professional.course
                                                                                         cellular
                                                                                                    nov
                                                                            no
                                                                                  no
                                                                   no
          41185
                   56
                          retired
                                  married
                                             university.degree
                                                                   no
                                                                            yes
                                                                                  no
                                                                                         cellular
                                                                                                    nov
          41186
                   44
                       technician
                                  married
                                          professional.course
                                                                                         cellular
                                                                                                    nov
                                                                   no
                                                                            no
                                                                                  no
          41187
                  74
                          retired married professional.course
                                                                                         cellular
                                                                   no
                                                                            yes
                                                                                  no
                                                                                                    nov
         41188 rows × 21 columns
```

Возвращает названия всех столбцов в DataFrame

Возвращает основную информации о DataFrame для определения, есть ли нулевые значения

```
In [4]: df.info()
          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 41188 entries, 0 to 41187
          Data columns (total 21 columns):
                Column
                                  Non-Null Count Dtype
               -----
                                   -----
                                   41188 non-null int64
           0
               age
               age
job
           1
                                  41188 non-null object
           2 marital 41188 non-null object
3 education 41188 non-null object
4 default 41188 non-null object
5 housing 41188 non-null object
           b loan 41188 non-null object object 7 contact 41188 non-null object 8 month 41188 non-null
           8 month 41188 non-null object
9 day_of_week 41188 non-null object
10 duration 41188 non-null int64
           11 campaign12 pdays
                                  41188 non-null int64
                                  41188 non-null int64
           13 previous 41188 non-null int64
14 poutcome 41188 non-null object
           15 emp.var.rate 41188 non-null float64
           16 cons.price.idx 41188 non-null float64
           17 cons.conf.idx 41188 non-null float64
           18 euribor3m
                                   41188 non-null float64
           19 nr.employed
                                  41188 non-null float64
           20 y
                                   41188 non-null object
          dtypes: float64(5), int64(5), object(11)
          memory usage: 6.6+ MB
```

Возвращает уникальные значения

```
In [5]: df['y'].unique()
Out[5]: array(['no', 'yes'], dtype=object)
```

Подсчет количества значений

```
In [6]: df['y'].value_counts()
Out[6]: no    36548
    yes    4640
    Name: y, dtype: int64
```

Перекодировка целевого столбца в бинарные значения и удаление исходного столбца:

df[['marital','Marital Binary']].head(41188)

```
Out[8]:
                 marital Marital Binary
              0 married
                                    1
                                    1
              1 married
                                    1
              2 married
              3 married
                                    1
                                    1
              4 married
          41183 married
                                    1
          41184 married
          41185 married
                                    1
          41186 married
                                    1
          41187 married
                                    1
         41188 rows × 2 columns
          df['default'].value_counts()
 In [9]:
                      32588
          no
 Out[9]:
                       8597
          unknown
          Name: default, dtype: int64
          risk_dictionary_binary_class = {'yes': 1,'no': 0, 'unknown': 0}
In [10]:
          df['Default Binary'] = df['default'].map(risk_dictionary_binary_class)
          df[['default','Default Binary']].head(41188)
Out[10]:
                  default Default Binary
              0
                                      0
                      no
                 unknown
                                      0
              2
                                      0
                      no
                      no
                                      0
              4
                                      0
                      no
          41183
                                      0
                      no
          41184
                                      0
                      no
          41185
                                      0
                      no
          41186
                                      0
          41187
                                      0
                      no
         41188 rows × 2 columns
```

df['housing'].value_counts()

In [11]:

```
Out[11]: yes 21576
no 18622
unknown 990
```

Name: housing, dtype: int64

In [12]: risk_dictionary_binary_class = {'yes': 1,'no': 0, 'unknown': 0}
df['Housing Binary'] = df['housing'].map(risk_dictionary_binary_class)
df[['housing','Housing Binary']].head(41188)

Out[12]:		housing	Housing Binary
	0	no	0
	1	no	0
	2	yes	1
	3	no	0
	4	no	0
	•••		
	41183	yes	1
	41184	no	0
	41185	yes	1
	41186	no	0
	41187	yes	1

41188 rows × 2 columns

Out[14]:		loan	Loan Binary
	0	no	0
	1	no	0
	2	no	0
	3	no	0
	4	yes	1
	•••		
	41183	no	0
	41184	no	0
	41185	no	0
	41186	no	0
	41187	no	0

41188 rows × 2 columns

ut[16]:		poutcome	Poutcome Binary
	0	nonexistent	1
	1	nonexistent	1
	2	nonexistent	1
	3	nonexistent	1
	4	nonexistent	1
	41183	nonexistent	1
	41184	nonexistent	1
	41185	nonexistent	1
	41186	nonexistent	1
	41187	failure	0

41188 rows × 2 columns

Перекодировка целевого столбца 'у' в бинарные значения и удаление исходного столбца 'у':

```
In [17]: risk_dictionary_binary_class = {'yes': 1, 'no': 0}
    df['Target Binary'] = df['y'].map(risk_dictionary_binary_class)
    df[['y','Target Binary']].head(41188)
```

Out[17]:		у	Target Binary
	0	no	0
	1	no	0
	2	no	0
	3	no	0
	4	no	0
	•••		
	41183	yes	1
	41184	no	0
	41185	no	0
	41186	yes	1
	41187	no	0

41188 rows × 2 columns

```
In [18]: X = df.drop(['y','job','education','marital','education','default','housing','loan'
y = df['Target Binary']
```

In [19]: print(y.isnull().sum())

0

In [20]: 2

Out[20]:

•		age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euri
	0	56	261	1	999	0	1.1	93.994	-36.4	
	1	57	149	1	999	0	1.1	93.994	-36.4	
	2	37	226	1	999	0	1.1	93.994	-36.4	
	3	40	151	1	999	0	1.1	93.994	-36.4	
	4	56	307	1	999	0	1.1	93.994	-36.4	
	•••									
	41183	73	334	1	999	0	-1.1	94.767	-50.8	
	41184	46	383	1	999	0	-1.1	94.767	-50.8	
	41185	56	189	2	999	0	-1.1	94.767	-50.8	
	41186	44	442	1	999	0	-1.1	94.767	-50.8	
	41187	74	239	3	999	1	-1.1	94.767	-50.8	

41188 rows × 15 columns

Преобразование категориальных данных с помощью и масштабирование данных:

```
In [33]: min_max_scaler = MinMaxScaler()
X_scaled = min_max_scaler.fit_transform(X)
```

Разделение данных на тренировочный, тестовый и валидационный наборы:

```
In [34]: X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size = {
    print(f'Train : {X_train.shape}, Test : {X_test.shape}')
    X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, stratify=y_train)
    print(f'Train : {X_train.shape}, Test : {X_val.shape}')

Train : (32950, 15), Test : (8238, 15)
Train : (26360, 15), Test : (6590, 15)
```

Обучение модели с использованием Keras. Создание модели нейронной сети, ее компиляция:

```
In [35]: binary_classifier = Sequential()
    binary_classifier.add(Dense(units=4,activation='relu',input_dim=15))
    binary_classifier.add(Dense(units=1,activation='sigmoid'))
```

In [36]: binary_classifier.summary()

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_2 (Dense)	(None, 4)	64
dense_3 (Dense)	(None, 1)	5

Total params: 69 (276.00 Byte)
Trainable params: 69 (276.00 Byte)
Non-trainable params: 0 (0.00 Byte)

Обучение модели

```
Epoch 1/40
Epoch 1: val accuracy did not improve from 0.90926
y: 0.9050 - val_loss: 0.2057 - val_accuracy: 0.9061
Epoch 2/40
9047
Epoch 2: val accuracy did not improve from 0.90926
y: 0.9047 - val_loss: 0.2077 - val_accuracy: 0.9067
Epoch 3/40
2636/2636 [============== ] - ETA: 0s - loss: 0.2108 - accuracy: 0.
9068
Epoch 3: val_accuracy did not improve from 0.90926
y: 0.9068 - val_loss: 0.2113 - val_accuracy: 0.9036
Epoch 4/40
9064
Epoch 4: val_accuracy did not improve from 0.90926
y: 0.9065 - val_loss: 0.2137 - val_accuracy: 0.8947
Epoch 5/40
Epoch 5: val_accuracy did not improve from 0.90926
y: 0.9060 - val_loss: 0.2074 - val_accuracy: 0.9055
Epoch 6/40
9070
Epoch 6: val_accuracy did not improve from 0.90926
y: 0.9070 - val_loss: 0.2051 - val_accuracy: 0.9055
Epoch 7/40
9072
Epoch 7: val accuracy did not improve from 0.90926
y: 0.9069 - val_loss: 0.2185 - val_accuracy: 0.8954
Epoch 8/40
Epoch 8: val_accuracy did not improve from 0.90926
y: 0.9058 - val_loss: 0.2053 - val_accuracy: 0.9041
Epoch 9/40
Epoch 9: val_accuracy did not improve from 0.90926
y: 0.9064 - val_loss: 0.2072 - val_accuracy: 0.9067
Epoch 10/40
9055
Epoch 10: val accuracy did not improve from 0.90926
y: 0.9056 - val_loss: 0.2080 - val_accuracy: 0.9067
Epoch 11/40
Epoch 11: val_accuracy did not improve from 0.90926
```

```
y: 0.9065 - val_loss: 0.2059 - val_accuracy: 0.9070
Epoch 12/40
Epoch 12: val accuracy did not improve from 0.90926
y: 0.9068 - val_loss: 0.2077 - val_accuracy: 0.9076
Epoch 13/40
9064
Epoch 13: val_accuracy did not improve from 0.90926
y: 0.9063 - val_loss: 0.2079 - val_accuracy: 0.9024
Epoch 14/40
9053
Epoch 14: val_accuracy did not improve from 0.90926
y: 0.9052 - val_loss: 0.2065 - val_accuracy: 0.9071
Epoch 15/40
9066
Epoch 15: val accuracy did not improve from 0.90926
y: 0.9066 - val_loss: 0.2052 - val_accuracy: 0.9067
Epoch 16/40
9064
Epoch 16: val_accuracy did not improve from 0.90926
y: 0.9065 - val_loss: 0.2089 - val_accuracy: 0.9032
Epoch 17/40
9064
Epoch 17: val_accuracy did not improve from 0.90926
y: 0.9064 - val_loss: 0.2070 - val_accuracy: 0.9035
Epoch 18/40
9062
Epoch 18: val accuracy did not improve from 0.90926
y: 0.9061 - val loss: 0.2063 - val accuracy: 0.9071
Epoch 19/40
Epoch 19: val_accuracy did not improve from 0.90926
y: 0.9060 - val loss: 0.2067 - val accuracy: 0.9074
Epoch 20/40
Epoch 20: val_accuracy did not improve from 0.90926
y: 0.9058 - val_loss: 0.2192 - val_accuracy: 0.8933
Epoch 21/40
9071
Epoch 21: val_accuracy did not improve from 0.90926
y: 0.9071 - val loss: 0.2117 - val accuracy: 0.9009
Epoch 22/40
```

9064

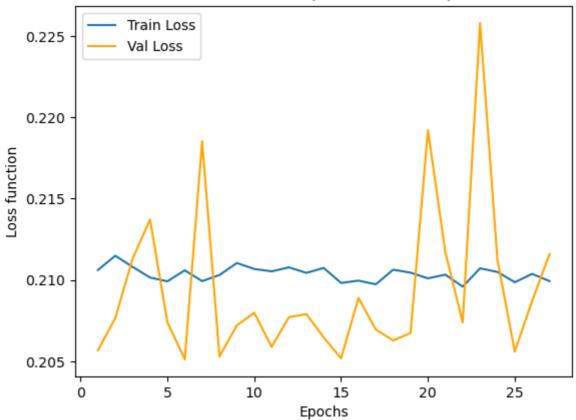
```
Epoch 22: val_accuracy did not improve from 0.90926
y: 0.9064 - val_loss: 0.2074 - val_accuracy: 0.9062
Epoch 23/40
2636/2636 [============= ] - ETA: 0s - loss: 0.2107 - accuracy: 0.
Epoch 23: val_accuracy did not improve from 0.90926
y: 0.9060 - val_loss: 0.2258 - val_accuracy: 0.9070
Epoch 24/40
Epoch 24: val_accuracy did not improve from 0.90926
y: 0.9063 - val_loss: 0.2113 - val_accuracy: 0.9074
Epoch 25/40
9061
Epoch 25: val_accuracy did not improve from 0.90926
y: 0.9060 - val_loss: 0.2056 - val_accuracy: 0.9067
Epoch 26/40
Epoch 26: val_accuracy did not improve from 0.90926
y: 0.9053 - val_loss: 0.2087 - val_accuracy: 0.9002
Epoch 27/40
9060
Epoch 27: val accuracy did not improve from 0.90926
y: 0.9060 - val_loss: 0.2116 - val_accuracy: 0.9058
Epoch 27: early stopping
```

Построение графика потери

```
In [55]: loss_function = binary_classifier_history.history['loss']
    val_loss_function = binary_classifier_history.history['val_loss']
    epochs = range(1,len(loss_function)+1)

plt.title('Loss function (Train & Val Sets)')
    plt.plot(epochs,loss_function,label='Train Loss')
    plt.plot(epochs,val_loss_function,color='orange',label='Val Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss function')
    plt.legend()
    plt.show()
```

Loss function (Train & Val Sets)

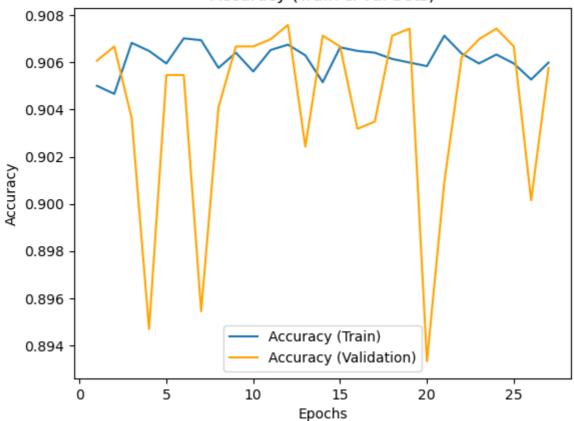


Построение графика точности в процессе обучения

```
In [56]: acc = binary_classifier_history.history['accuracy']
    val_acc = binary_classifier_history.history['val_accuracy']
    epochs = range(1,len(acc)+1)

    plt.title('Accuracy (Train & Val Sets)')
    plt.plot(epochs,acc,label='Accuracy (Train)')
    plt.plot(epochs,val_acc,color='orange',label='Accuracy (Validation)')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.show()
```

Accuracy (Train & Val Sets)



Тестирование модели на тестовых данных и предсказание класса для конкретного образца:

```
# Load a saved model
In [57]:
        #from keras.models import load model
        #saved_model = load_model('best_model.h5')
        binary_classifier.load_weights('C:/Users/vvadi/DeepLearning/Binary_Classifier-19-0.
In [58]:
        results = binary_classifier.evaluate(X_test,y_test)
        0.9093
In [59]:
        #x_test_pattern = X_test[1,:]
        #y_pred = binary_classifier.predict(x_test_pattern.reshape(1,-1))
        x_test_pattern = X_test.iloc[1]
        x_test_pattern = x_test_pattern.values.reshape(1,-1)
        y_pred = binary_classifier.predict(x_test_pattern)
        print(y_pred[0])
        1/1 [=======] - 0s 50ms/step
        [0.00019114]
In [60]:
       y_test
```

```
17589
Out[60]:
         3158
                 0
         2118
                  0
         12435
         13939
                 0
         33427
         32280
                 a
         25947
                 0
         13050
         39975
         Name: Target Binary, Length: 8238, dtype: int64
In [61]: print(x_test_pattern)
         [[ 5.2000e+01 3.6000e+01 1.0000e+00 9.9900e+02 0.0000e+00
                                                                      1.1000e+00
            9.3994e+01 -3.6400e+01 4.8600e+00 5.1910e+03 1.0000e+00
            1.0000e+00 0.0000e+00 1.0000e+00]
```

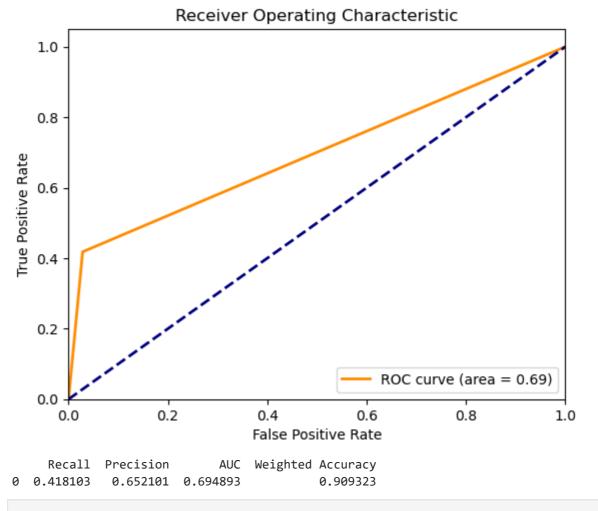
Возврат особенностей тестового набора данных к их исходному масштабу:

Метрики работы Recall, Precision, Weighted Accuracy, AUC

```
In [63]: from sklearn.metrics import recall_score, precision_score, roc_auc_score, confusion
         # Делаем предсказания
         y pred = binary classifier.predict(X test)
         #y pred = np.round(y pred)
         y_pred = (y_pred > 0.5).astype(int).reshape(y_test.shape)
         # Вычисляем метрики
         recall = recall_score(y_test, y_pred)
         precision = precision_score(y_test, y_pred)
         auc = roc_auc_score(y_test, y_pred)
         # Вычисляем ассигасу для каждого класса и получаем средневзвешенное значение
         cm = confusion_matrix(y_test, y_pred)
         class wise = cm.diagonal()/cm.sum(axis=1)
         weighted_accuracy = np.average(class_wise, weights=cm.sum(axis=1))
         print(f"Recall: {recall}\nPrecision: {precision}\nAUC: {auc}\nWeighted Accuracy: {v
         258/258 [========== ] - 1s 3ms/step
         Recall: 0.41810344827586204
         Precision: 0.6521008403361345
         AUC: 0.6948930374074249
         Weighted Accuracy: 0.9093226511289147
```

Расчет значений для ROC-кривой и AUC

```
In [64]:
         # Расчет значений для ROC-кривой и AUC
         fpr, tpr, _ = roc_curve(y_test, y_pred)
         # Построение ROC-кривой
         plt.figure()
         plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % aud
         plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
         plt.xlim([0.0, 1.0])
         plt.ylim([0.0, 1.05])
         plt.xlabel('False Positive Rate')
          plt.ylabel('True Positive Rate')
          plt.title('Receiver Operating Characteristic')
         plt.legend(loc="lower right")
         # Отображение ROC-кривой
         plt.show()
         # Отображение метрик в виде датафрейма
         metrics_df = pd.DataFrame(data={"Recall": [recall], "Precision": [precision], "AUC"
         print(metrics_df.head())
```



In []:

Лабораторная работа № 1

Боровских Вадим, 932003

B) Многоклассовый классификатор fetal_health.csv

```
In [21]: import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from keras.models import Sequential
from keras.layers import Dense
from keras.callbacks import ModelCheckpoint, EarlyStopping
In [22]: df = pd.read_csv("fetal_health.csv", quotechar='"', index_col = 0)
df=df.reset_index()
df
Out[22]: baseline
value accelerations fetal_movement uterine_contractions light_decelerations severe_decenter.
```

:		baseline value	accelerations	fetal_movement	uterine_contractions	light_decelerations	severe_dec
	0	120.0	0.000	0.000	0.000	0.000	
	1	132.0	0.006	0.000	0.006	0.003	
	2	133.0	0.003	0.000	0.008	0.003	
	3	134.0	0.003	0.000	0.008	0.003	
	4	132.0	0.007	0.000	0.008	0.000	
	•••						
	2121	140.0	0.000	0.000	0.007	0.000	
	2122	140.0	0.001	0.000	0.007	0.000	
	2123	140.0	0.001	0.000	0.007	0.000	
	2124	140.0	0.001	0.000	0.006	0.000	
	2125	142.0	0.002	0.002	0.008	0.000	

2126 rows × 22 columns

```
In [23]: df.columns
```

```
Index(['baseline value', 'accelerations', 'fetal_movement',
Out[23]:
                 'uterine_contractions', 'light_decelerations', 'severe_decelerations',
                 'prolongued_decelerations', 'abnormal_short_term_variability',
                 'mean_value_of_short_term_variability',
                 'percentage_of_time_with_abnormal_long_term_variability',
                 'mean_value_of_long_term_variability', 'histogram_width',
                 'histogram_min', 'histogram_max', 'histogram_number_of_peaks',
                 'histogram_number_of_zeroes', 'histogram_mode', 'histogram_mean',
                 'histogram_median', 'histogram_variance', 'histogram_tendency',
                 'fetal_health'],
               dtype='object')
In [24]:
         df['fetal_health'].unique()
         array([2., 1., 3.])
Out[24]:
          df['fetal_health'].value_counts()
In [25]:
         1.0
                 1655
Out[25]:
         2.0
                 295
                 176
         3.0
         Name: fetal_health, dtype: int64
         1 - соответствует нормальному состоянию плода, 2 - подозрительному состоянию
         плода,3 - патология
In [26]:
         df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
         RangeIndex: 2126 entries, 0 to 2125
         Data columns (total 22 columns):
              Column
                                                                        Non-Null Count Dtype
         _ _ _
              baseline value
          0
                                                                        2126 non-null
                                                                                        float
         64
              accelerations
                                                                        2126 non-null
          1
                                                                                        float
         64
          2
              fetal_movement
                                                                        2126 non-null
                                                                                        float
         64
          3
              uterine_contractions
                                                                        2126 non-null
                                                                                        float
         64
          4
              light_decelerations
                                                                        2126 non-null
                                                                                        float
         64
                                                                        2126 non-null
                                                                                        float
          5
              severe_decelerations
         64
               prolongued_decelerations
                                                                        2126 non-null
                                                                                        float
          6
         64
          7
              abnormal_short_term_variability
                                                                        2126 non-null
                                                                                        float
         64
              mean_value_of_short_term_variability
                                                                        2126 non-null
                                                                                        float
          8
         64
          9
               percentage_of_time_with_abnormal_long_term_variability 2126 non-null
                                                                                        float
         64
          10
              mean_value_of_long_term_variability
                                                                        2126 non-null
                                                                                        float
         64
              histogram_width
          11
                                                                        2126 non-null
                                                                                        float
         64
          12
              histogram_min
                                                                        2126 non-null
                                                                                        float
         64
                                                                        2126 non-null
                                                                                        float
          13
              histogram_max
         64
                                                                        2126 non-null
                                                                                        float
          14
              histogram_number_of_peaks
         64
          15
             histogram_number_of_zeroes
                                                                        2126 non-null
                                                                                        float
         64
          16
             histogram_mode
                                                                        2126 non-null
                                                                                        float
         64
          17
              histogram mean
                                                                        2126 non-null
                                                                                        float
         64
                                                                        2126 non-null
                                                                                        float
          18
              histogram median
         64
          19
              histogram_variance
                                                                        2126 non-null
                                                                                        float
         64
                                                                        2126 non-null
                                                                                        float
          20 histogram_tendency
         64
          21 fetal_health
                                                                        2126 non-null
                                                                                        float
         dtypes: float64(22)
         memory usage: 365.5 KB
         risk_dictionary_multi_class = {2:2, 1:1, 3:3}
In [27]:
         df['Target Multi'] = df['fetal_health'].map(risk_dictionary_multi_class)
         df[['fetal_health','Target Multi']].head()
```

2

fetal_health Target Multi

2.0

Out[28]:

0

```
1
                     1.0
                                  1
          2
                     1.0
                                  1
          3
                     1.0
          4
                     1.0
                                  1
In [29]: Xmc = df.drop(['fetal_health','Target Multi'],axis=1)
          y = df['Target Multi']
          У
                  2
Out[29]:
                  1
          2
                  1
          3
                  1
          4
                  1
                  . .
          2121
                  2
          2122
          2123
                 2
          2124
                  2
          2125
          Name: Target Multi, Length: 2126, dtype: int64
         print(y.isnull().sum())
In [30]:
          0
```

Преобразование категориальных данных с помощью get_dummies и масштабирование данных:

```
In [31]: from sklearn.preprocessing import MinMaxScaler
         min max scaler = MinMaxScaler()
         Xmc = min max scaler.fit transform(Xmc)
         from sklearn.model_selection import train_test_split
In [32]:
         X_all_train, X_test, y_all_train, y_test = train_test_split(Xmc, y, stratify=y, tes
         print(f'Train : {X_all_train.shape}, Test : {X_test.shape}')
         Train: (1700, 21), Test: (426, 21)
In [33]: X_train, X_val, y_train, y_val = train_test_split(X_all_train, y_all_train, stratif
         print(f'Train : {X_train.shape}, Test : {X_val.shape}')
         Train: (1360, 21), Test: (340, 21)
In [34]: from tensorflow.keras.utils import to_categorical
         y_train = to_categorical(y_train)
         y_val = to_categorical(y_val)
         y_test = to_categorical(y_test)
         print('y_train shape:', y_train.shape)
         print('y_val shape:', y_val.shape)
         print('y_test shape:', y_test.shape)
         y_train shape: (1360, 4)
         y_val shape: (340, 4)
         y_test shape: (426, 4)
```

```
Epoch 1/50
68/68 [============= ] - 2s 12ms/step - loss: 1.1452 - accuracy:
0.5529 - val_loss: 0.8608 - val_accuracy: 0.7824
Epoch 2/50
68/68 [============] - 0s 5ms/step - loss: 0.7402 - accuracy: 0.
7801 - val loss: 0.6669 - val accuracy: 0.7794
68/68 [============] - 0s 5ms/step - loss: 0.6268 - accuracy: 0.
7794 - val_loss: 0.5896 - val_accuracy: 0.7882
Epoch 4/50
68/68 [============] - 0s 5ms/step - loss: 0.5657 - accuracy: 0.
7824 - val_loss: 0.5375 - val_accuracy: 0.7853
Epoch 5/50
68/68 [============] - 0s 6ms/step - loss: 0.5250 - accuracy: 0.
7860 - val loss: 0.4998 - val accuracy: 0.7912
Epoch 6/50
68/68 [============] - 0s 5ms/step - loss: 0.4913 - accuracy: 0.
7956 - val_loss: 0.4721 - val_accuracy: 0.7882
Epoch 7/50
68/68 [============] - 0s 5ms/step - loss: 0.4654 - accuracy: 0.
8081 - val_loss: 0.4489 - val_accuracy: 0.8176
Epoch 8/50
68/68 [============ ] - 0s 5ms/step - loss: 0.4431 - accuracy: 0.
8206 - val_loss: 0.4288 - val_accuracy: 0.8265
Epoch 9/50
68/68 [============] - 0s 6ms/step - loss: 0.4236 - accuracy: 0.
8250 - val_loss: 0.4125 - val_accuracy: 0.8294
Epoch 10/50
68/68 [============ ] - 0s 6ms/step - loss: 0.4075 - accuracy: 0.
8360 - val_loss: 0.3983 - val_accuracy: 0.8265
Epoch 11/50
68/68 [============ ] - 0s 6ms/step - loss: 0.3920 - accuracy: 0.
8434 - val loss: 0.3860 - val accuracy: 0.8324
Epoch 12/50
68/68 [============] - 0s 5ms/step - loss: 0.3798 - accuracy: 0.
8463 - val_loss: 0.3762 - val_accuracy: 0.8382
Epoch 13/50
68/68 [============= ] - 0s 6ms/step - loss: 0.3684 - accuracy: 0.
8507 - val_loss: 0.3669 - val_accuracy: 0.8382
Epoch 14/50
68/68 [============ ] - 0s 5ms/step - loss: 0.3597 - accuracy: 0.
8507 - val_loss: 0.3594 - val_accuracy: 0.8412
Epoch 15/50
68/68 [============ ] - 0s 5ms/step - loss: 0.3506 - accuracy: 0.
8596 - val_loss: 0.3521 - val_accuracy: 0.8441
Epoch 16/50
68/68 [============] - 0s 5ms/step - loss: 0.3429 - accuracy: 0.
8559 - val_loss: 0.3461 - val_accuracy: 0.8441
Epoch 17/50
68/68 [============ ] - 0s 6ms/step - loss: 0.3361 - accuracy: 0.
8551 - val loss: 0.3400 - val accuracy: 0.8559
Epoch 18/50
68/68 [============ ] - 0s 5ms/step - loss: 0.3302 - accuracy: 0.
8632 - val_loss: 0.3353 - val_accuracy: 0.8441
Epoch 19/50
68/68 [============ ] - 0s 5ms/step - loss: 0.3248 - accuracy: 0.
8551 - val_loss: 0.3297 - val_accuracy: 0.8588
Epoch 20/50
68/68 [============ ] - 0s 5ms/step - loss: 0.3204 - accuracy: 0.
8581 - val_loss: 0.3258 - val_accuracy: 0.8588
Epoch 21/50
68/68 [============ ] - 0s 6ms/step - loss: 0.3153 - accuracy: 0.
8618 - val_loss: 0.3213 - val_accuracy: 0.8618
Epoch 22/50
```

```
68/68 [============] - 0s 5ms/step - loss: 0.3108 - accuracy: 0.
8654 - val_loss: 0.3174 - val_accuracy: 0.8618
Epoch 23/50
68/68 [============] - 0s 5ms/step - loss: 0.3067 - accuracy: 0.
8632 - val_loss: 0.3139 - val_accuracy: 0.8588
Epoch 24/50
68/68 [============] - 0s 5ms/step - loss: 0.3026 - accuracy: 0.
8669 - val_loss: 0.3123 - val_accuracy: 0.8588
Epoch 25/50
68/68 [============ ] - 0s 6ms/step - loss: 0.3019 - accuracy: 0.
8647 - val_loss: 0.3073 - val_accuracy: 0.8588
Epoch 26/50
68/68 [============] - 0s 5ms/step - loss: 0.2968 - accuracy: 0.
8640 - val_loss: 0.3042 - val_accuracy: 0.8618
Epoch 27/50
68/68 [============ ] - 0s 5ms/step - loss: 0.2939 - accuracy: 0.
8684 - val_loss: 0.3024 - val_accuracy: 0.8618
Epoch 28/50
68/68 [===========] - 0s 6ms/step - loss: 0.2910 - accuracy: 0.
8676 - val_loss: 0.2989 - val_accuracy: 0.8735
Epoch 29/50
68/68 [============] - 0s 6ms/step - loss: 0.2884 - accuracy: 0.
8728 - val_loss: 0.2965 - val_accuracy: 0.8735
Epoch 30/50
68/68 [============] - 0s 6ms/step - loss: 0.2862 - accuracy: 0.
8757 - val_loss: 0.2956 - val_accuracy: 0.8647
Epoch 31/50
68/68 [============] - 0s 6ms/step - loss: 0.2839 - accuracy: 0.
8757 - val_loss: 0.2924 - val_accuracy: 0.8765
Epoch 32/50
68/68 [============] - 0s 5ms/step - loss: 0.2811 - accuracy: 0.
8772 - val_loss: 0.2911 - val_accuracy: 0.8765
Epoch 33/50
68/68 [============] - 0s 6ms/step - loss: 0.2802 - accuracy: 0.
8787 - val_loss: 0.2887 - val_accuracy: 0.8765
Epoch 34/50
68/68 [============] - 0s 6ms/step - loss: 0.2779 - accuracy: 0.
8779 - val_loss: 0.2866 - val_accuracy: 0.8824
Epoch 35/50
68/68 [===========] - 0s 5ms/step - loss: 0.2755 - accuracy: 0.
8801 - val loss: 0.2846 - val accuracy: 0.8765
Epoch 36/50
68/68 [============ ] - 0s 5ms/step - loss: 0.2741 - accuracy: 0.
8801 - val loss: 0.2822 - val accuracy: 0.8824
Epoch 37/50
68/68 [============] - 0s 6ms/step - loss: 0.2720 - accuracy: 0.
8824 - val_loss: 0.2814 - val_accuracy: 0.8912
Epoch 38/50
68/68 [============ ] - 0s 6ms/step - loss: 0.2703 - accuracy: 0.
8824 - val loss: 0.2793 - val accuracy: 0.8912
Epoch 39/50
68/68 [===========] - 0s 5ms/step - loss: 0.2694 - accuracy: 0.
8846 - val_loss: 0.2800 - val_accuracy: 0.8706
Epoch 40/50
68/68 [============= ] - 0s 6ms/step - loss: 0.2675 - accuracy: 0.
8824 - val_loss: 0.2783 - val_accuracy: 0.8941
Epoch 41/50
68/68 [============ ] - 0s 6ms/step - loss: 0.2662 - accuracy: 0.
8831 - val_loss: 0.2766 - val_accuracy: 0.8941
Epoch 42/50
68/68 [===========] - 0s 7ms/step - loss: 0.2644 - accuracy: 0.
8838 - val loss: 0.2749 - val accuracy: 0.8971
Epoch 43/50
68/68 [============= ] - 0s 6ms/step - loss: 0.2633 - accuracy: 0.
```

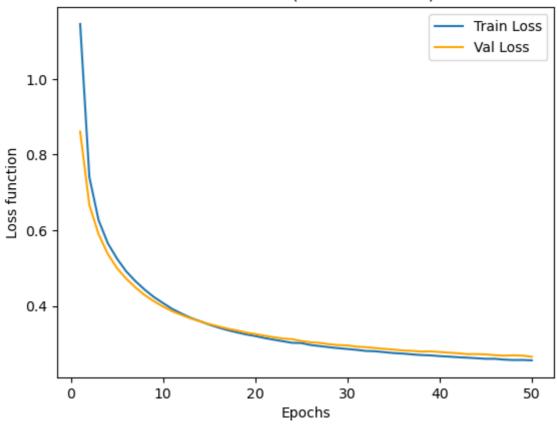
```
8846 - val_loss: 0.2726 - val_accuracy: 0.8853
Epoch 44/50
68/68 [============] - 0s 5ms/step - loss: 0.2619 - accuracy: 0.
8868 - val_loss: 0.2728 - val_accuracy: 0.8941
Epoch 45/50
68/68 [============ ] - 0s 6ms/step - loss: 0.2604 - accuracy: 0.
8882 - val_loss: 0.2719 - val_accuracy: 0.8941
Epoch 46/50
68/68 [============] - 0s 6ms/step - loss: 0.2603 - accuracy: 0.
8868 - val_loss: 0.2699 - val_accuracy: 0.8941
Epoch 47/50
68/68 [============] - 0s 6ms/step - loss: 0.2582 - accuracy: 0.
8912 - val_loss: 0.2686 - val_accuracy: 0.8882
Epoch 48/50
68/68 [============ - 0s 6ms/step - loss: 0.2571 - accuracy: 0.
8875 - val_loss: 0.2695 - val_accuracy: 0.8971
Epoch 49/50
68/68 [============ ] - 1s 8ms/step - loss: 0.2572 - accuracy: 0.
8897 - val_loss: 0.2688 - val_accuracy: 0.8941
Epoch 50/50
68/68 [============] - 0s 5ms/step - loss: 0.2563 - accuracy: 0.
8890 - val_loss: 0.2656 - val_accuracy: 0.8882
```

Построение графика потери

```
In [38]: loss_function = multi_classifier_history.history['loss']
    val_loss_function = multi_classifier_history.history['val_loss']
    epochs = range(1,len(loss_function)+1)

plt.title('Loss function (Train & Val Sets)')
    plt.plot(epochs,loss_function,label='Train Loss')
    plt.plot(epochs,val_loss_function,color='orange',label='Val Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss function')
    plt.legend()
    plt.show()
```

Loss function (Train & Val Sets)

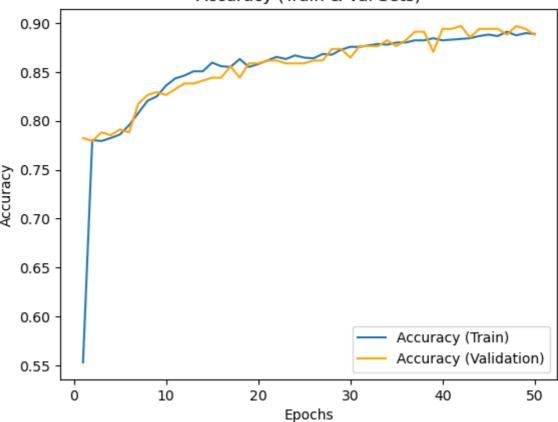


Построение графика точности

```
In [39]: acc = multi_classifier_history.history['accuracy']
    val_acc = multi_classifier_history.history['val_accuracy']
    epochs = range(1,len(acc)+1)

    plt.title('Accuracy (Train & Val Sets)')
    plt.plot(epochs,acc,label='Accuracy (Train)')
    plt.plot(epochs,val_acc,color='orange',label='Accuracy (Validation)')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.show()
```

Accuracy (Train & Val Sets)



```
print(y_test[4])
In [40]:
         [0. 1. 0. 0.]
In [50]: x_test_pattern = X_test[4,:]
         original_features= min_max_scaler.inverse_transform(x_test_pattern.reshape(1,-1))
         print(original_features)
         y_pred = multi_classifier.predict(x_test_pattern.reshape(1,-1))
         [[1.52e+02 0.00e+00 0.00e+00 5.00e-03 0.00e+00 0.00e+00 0.00e+00 6.20e+01
           4.00e-01 5.90e+01 5.60e+00 2.50e+01 1.36e+02 1.61e+02 0.00e+00 0.00e+00
           1.59e+02 1.56e+02 1.58e+02 1.00e+00 1.00e+00]]
         1/1 [=======] - 0s 58ms/step
         from sklearn.preprocessing import label binarize
In [51]:
         import numpy as np
         y_bin = label_binarize(y, classes=np.unique(y))
         n_classes = y_bin.shape[1]
In [52]:
         X = Xmc
         X_train, X_test, y_train, y_test = train_test_split(X, y_bin, test_size=.2, random_
         print('Shape of X:', X.shape)
         print('Shape of y_bin:', y_bin.shape)
         Shape of X: (2126, 21)
         Shape of y_bin: (2126, 3)
```

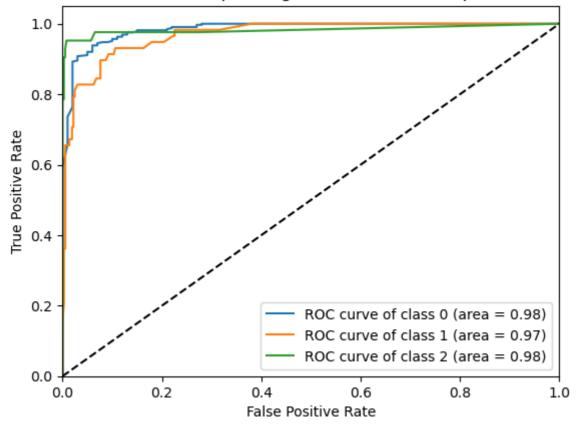
Построение ROC-кривой

```
In [53]: from sklearn.multiclass import OneVsRestClassifier
    from sklearn.ensemble import RandomForestClassifier
```

```
classifier = OneVsRestClassifier(RandomForestClassifier())
y_score = classifier.fit(X_train, y_train).predict_proba(X_test)
```

```
from sklearn.metrics import roc_curve, auc
In [54]:
         fpr = dict()
         tpr = dict()
         roc_auc = dict()
         for i in range(n_classes):
             fpr[i], tpr[i], _ = roc_curve(y_test[:, i], y_score[:, i])
              roc_auc[i] = auc(fpr[i], tpr[i])
         # Plot ROC кривые
         plt.figure()
         for i in range(n_classes):
             plt.plot(fpr[i], tpr[i], label='ROC curve of class {0} (area = {1:0.2f})'.forma
         # Добавление случайной диагонали
         plt.plot([0, 1], [0, 1], 'k--')
         plt.xlim([0.0, 1.0])
         plt.ylim([0.0, 1.05])
         plt.xlabel('False Positive Rate')
         plt.ylabel('True Positive Rate')
         plt.title('Receiver operating characteristic example')
         plt.legend(loc="lower right")
         plt.show()
```

Receiver operating characteristic example



Метрики работы Recall, Precision, Weighted Accuracy, AUC

```
In [56]: from sklearn.metrics import precision_recall_fscore_support
```

```
classifier = OneVsRestClassifier(RandomForestClassifier())
y_score = classifier.fit(X_train, y_train).predict_proba(X_test)

y_pred = (y_score == y_score.max(axis=1)[:,None]).astype(int)

precision, recall, _, _ = precision_recall_fscore_support(y_test, y_pred, average='
auc = roc_auc_score(y_test, y_score, multi_class='ovr')

print("Precision: ", precision)
print("Recall: ", recall)
print("AUC: ", auc)

accuracy = accuracy_score(y_test, y_pred)
print("Weighted Accuracy: ", accuracy)
```

Precision: 0.9424434917086499 Recall: 0.9436619718309859 AUC: 0.9793782735877897

Weighted Accuracy: 0.9436619718309859

In []:

Лабораторная работа № 1

Боровских Вадим, 932003

C) Perpeccop DS_2019_public.csv

t[3]:		Climate_Region_Pub	DIVISION	REPORTABLE_DOMAIN	DOLELCOL	TOTALDOLCOL	KWHCO
	0	5	10	26	16.793	17	181.99
	1	1	1	1	48.901	49	184.45
	2	1	3	7	101.048	101	1063.027
	3	1	1	1	0	0	0.00
	4	1	4	10	45.132	45	274.53
	•••						
	10870	4	5	13	345.8	346	2695.62
	10871	1	3	9	13.005	13	97.49 ⁻
	10872	1	4	10	97.67	98	847.73
	10873	1	8	23	12.834	13	135.68 ⁻
	10874	5	10	26	0	0	0.00

10875 rows × 121 columns

int64 Climate_Region_Pub Out[6]: **DIVISION** int64 REPORTABLE_DOMAIN int64 DOLELCOL object TOTALDOLCOL int64 HEATROOM int64 WDWATER int64 **UGWARM** int64 DRYRFUEL int64 **KWHRFG** float64 Length: 121, dtype: object

In [6]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10875 entries, 0 to 10874

Columns: 121 entries, Climate_Region_Pub to KWHRFG

dtypes: float64(34), int64(79), object(8)

memory usage: 10.0+ MB

In [7]: df.describe()

ut[7]:		Climate_Region_Pub	DIVISION	REPORTABLE_DOMAIN	TOTALDOLCOL	KWHCOL	
	count	10875.000000	10875.000000	10875.000000	10875.000000	10875.000000	1
	mean	2.601195	5.371034	14.778391	202.429333	1682.782696	
	std	1.349507	2.862200	8.207299	310.691148	2480.831034	
	min	1.000000	1.000000	1.000000	0.000000	0.000000	
	25%	1.000000	3.000000	8.000000	18.000000	143.161500	
	50%	3.000000	5.000000	15.000000	90.000000	748.220000	
	75%	4.000000	7.000000	21.000000	263.000000	2281.322500	
	max	5.000000	10.000000	27.000000	7729.000000	60995.431000	20

8 rows × 113 columns

```
In [11]: from sklearn.preprocessing import MinMaxScaler

# Удалите строки с некорректными значениями

df = df[~df.apply(lambda row: row.astype(str).str.contains('[^0-9.]').any(), axis=1

# Затем быполните масштабирование

X = df.drop(['TOTALBTUCOL'], axis=1)

y = df['TOTALBTUCOL']

min_max_scaler = MinMaxScaler()

X = min_max_scaler.fit_transform(X)
```

Разделение данных на обучающую и тестовую выборки

```
In [12]: X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size=0.2, ra
X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val, test_si
print(f'Train : {X_train_val.shape}, Test : {X_test.shape}')
print(f'Train : {X_train.shape}, Test : {X_val.shape}')
Train : (3976 120) Test : (995 120)
```

Train: (3976, 120), Test: (995, 120) Train: (3180, 120), Test: (796, 120)

Построение модели

```
In [15]: from keras.models import Sequential
         from keras.layers import Dense
         regressor = Sequential()
         regressor.add(Dense(120, activation='relu', input_dim=X_train.shape[1]))
          regressor.add(Dense(60,activation='relu'))
          regressor.add(Dense(1,activation='linear'))
         regressor.summary()
         Model: "sequential"
          Layer (type)
                                      Output Shape
                                                                 Param #
         ===============
          dense (Dense)
                                      (None, 120)
                                                                 14520
          dense_1 (Dense)
                                      (None, 60)
                                                                 7260
          dense_2 (Dense)
                                      (None, 1)
                                                                 61
         Total params: 21841 (85.32 KB)
         Trainable params: 21841 (85.32 KB)
         Non-trainable params: 0 (0.00 Byte)
In [16]: regressor.compile(loss='mse', optimizer='adam', metrics='mae')
In [19]: from keras.callbacks import ModelCheckpoint, EarlyStopping
         early_stop = EarlyStopping(monitor='val_loss', patience=20, mode='min', verbose=1)
         checkpoint = ModelCheckpoint('regressor_weights-{epoch:02d}-{val_loss:.3f}.hdf5',
         monitor='val_loss', verbose=1, mode='min', save_best_only=True)
         callbacks_list = [early_stop, checkpoint]
```

Обучение модели

```
In [30]:
       regressor history = regressor.fit(X train, y train, batch size=40, validation data=
       callbacks=callbacks_list, epochs=350)
       Epoch 1/350
       Epoch 1: val_loss improved from 91159.12500 to 88805.09375, saving model to regres
       sor weights-01-88805.094.hdf5
       8.3285 - val loss: 88805.0938 - val mae: 185.0776
       Epoch 2/350
       36/80 [=======>>.....] - ETA: 0s - loss: 83602.2031 - mae: 185.729
       D:\Anaconda\lib\site-packages\keras\src\engine\training.py:3079: UserWarning: You
       are saving your model as an HDF5 file via `model.save()`. This file format is cons
       idered legacy. We recommend using instead the native Keras format, e.g. `model.sav
       e('my model.keras')`.
       saving api.save model(
```

```
Epoch 2: val_loss improved from 88805.09375 to 85150.42969, saving model to regres
sor weights-02-85150.430.hdf5
80/80 [============= - 1s 6ms/step - loss: 78983.8438 - mae: 17
7.4560 - val loss: 85150.4297 - val mae: 181.1830
Epoch 3/350
Epoch 3: val_loss did not improve from 85150.42969
8.4410 - val_loss: 87148.1172 - val_mae: 180.1727
Epoch 4/350
80/80 [==========] - ETA: 0s - loss: 79679.9922 - mae: 180.144
Epoch 4: val_loss did not improve from 85150.42969
0.1443 - val_loss: 86781.7891 - val_mae: 186.2940
Epoch 5/350
Epoch 5: val_loss improved from 85150.42969 to 84595.46875, saving model to regres
sor weights-05-84595.469.hdf5
8.3729 - val_loss: 84595.4688 - val_mae: 185.1752
Epoch 6/350
Epoch 6: val_loss improved from 84595.46875 to 82687.78906, saving model to regres
sor_weights-06-82687.789.hdf5
80/80 [============] - 1s 6ms/step - loss: 78482.8750 - mae: 18
1.9034 - val loss: 82687.7891 - val mae: 175.8157
Epoch 7/350
Epoch 7: val_loss did not improve from 82687.78906
5.3165 - val_loss: 103552.0469 - val_mae: 213.1767
Epoch 8/350
Epoch 8: val_loss did not improve from 82687.78906
5.5081 - val loss: 84574.2500 - val mae: 180.5268
Epoch 9/350
69/80 [============>....] - ETA: 0s - loss: 72191.5859 - mae: 168.914
Epoch 9: val_loss improved from 82687.78906 to 77789.17188, saving model to regres
sor weights-09-77789.172.hdf5
80/80 [============ - 1s 7ms/step - loss: 71530.8047 - mae: 16
9.1565 - val_loss: 77789.1719 - val_mae: 169.7033
Epoch 10/350
Epoch 10: val_loss improved from 77789.17188 to 77667.42969, saving model to regre
ssor weights-10-77667.430.hdf5
8.6423 - val_loss: 77667.4297 - val_mae: 172.3755
Epoch 11/350
80/80 [===========] - ETA: 0s - loss: 72958.1797 - mae: 173.219
Epoch 11: val loss improved from 77667.42969 to 76288.79688, saving model to regre
ssor_weights-11-76288.797.hdf5
```

```
3.2192 - val_loss: 76288.7969 - val_mae: 168.5740
Epoch 12/350
Epoch 12: val_loss did not improve from 76288.79688
80/80 [============ - 1s 7ms/step - loss: 74355.3984 - mae: 17
6.7285 - val_loss: 83019.6562 - val_mae: 180.9560
Epoch 13/350
Epoch 13: val_loss improved from 76288.79688 to 74600.02344, saving model to regre
ssor_weights-13-74600.023.hdf5
8.6737 - val_loss: 74600.0234 - val_mae: 165.9403
Epoch 14/350
Epoch 14: val_loss improved from 74600.02344 to 72241.75000, saving model to regre
ssor_weights-14-72241.750.hdf5
4.3043 - val_loss: 72241.7500 - val_mae: 166.2406
Epoch 15/350
Epoch 15: val_loss improved from 72241.75000 to 71819.93750, saving model to regre
ssor_weights-15-71819.938.hdf5
2.5640 - val_loss: 71819.9375 - val_mae: 161.8786
Epoch 16/350
Epoch 16: val_loss improved from 71819.93750 to 71477.77344, saving model to regre
ssor weights-16-71477.773.hdf5
2.9917 - val_loss: 71477.7734 - val_mae: 165.0567
Epoch 17/350
Epoch 17: val_loss did not improve from 71477.77344
1.8394 - val loss: 71626.0156 - val mae: 170.4307
Epoch 18/350
Epoch 18: val_loss improved from 71477.77344 to 70259.39062, saving model to regre
ssor_weights-18-70259.391.hdf5
80/80 [============ - - 1s 8ms/step - loss: 64039.8320 - mae: 16
2.2730 - val_loss: 70259.3906 - val_mae: 161.1354
Epoch 19/350
Epoch 19: val_loss did not improve from 70259.39062
2.3914 - val_loss: 73111.5391 - val_mae: 172.5299
Epoch 20/350
Epoch 20: val loss improved from 70259.39062 to 67537.35156, saving model to regre
ssor weights-20-67537.352.hdf5
80/80 [============= - 15 7ms/step - loss: 65368.4375 - mae: 16
6.8807 - val_loss: 67537.3516 - val_mae: 161.0040
Epoch 21/350
```

```
Epoch 21: val loss did not improve from 67537.35156
7.6233 - val_loss: 67968.9453 - val_mae: 160.5246
Epoch 22/350
Epoch 22: val_loss did not improve from 67537.35156
2.2133 - val_loss: 69238.6719 - val_mae: 159.9018
Epoch 23/350
Epoch 23: val_loss improved from 67537.35156 to 67009.60938, saving model to regre
ssor_weights-23-67009.609.hdf5
80/80 [============ - 15 8ms/step - loss: 61455.5273 - mae: 15
8.4510 - val loss: 67009.6094 - val mae: 163.6099
Epoch 24/350
Epoch 24: val_loss improved from 67009.60938 to 64633.08594, saving model to regre
ssor_weights-24-64633.086.hdf5
80/80 [============= - 1s 7ms/step - loss: 59278.0078 - mae: 15
6.4514 - val_loss: 64633.0859 - val_mae: 155.2231
Epoch 25/350
Epoch 25: val_loss improved from 64633.08594 to 64130.80469, saving model to regre
ssor_weights-25-64130.805.hdf5
7.9673 - val_loss: 64130.8047 - val_mae: 159.8861
Epoch 26/350
Epoch 26: val_loss did not improve from 64130.80469
5.7728 - val_loss: 64501.2852 - val_mae: 159.7588
Epoch 27/350
Epoch 27: val loss did not improve from 64130.80469
3.0820 - val_loss: 72671.1328 - val_mae: 180.3934
Epoch 28/350
Epoch 28: val_loss improved from 64130.80469 to 60796.83594, saving model to regre
ssor weights-28-60796.836.hdf5
4.0440 - val loss: 60796.8359 - val mae: 150.3739
Epoch 29/350
Epoch 29: val loss improved from 60796.83594 to 60175.47656, saving model to regre
ssor weights-29-60175.477.hdf5
80/80 [============] - 1s 8ms/step - loss: 54665.5508 - mae: 14
9.3056 - val_loss: 60175.4766 - val_mae: 154.5913
Epoch 30/350
Epoch 30: val_loss did not improve from 60175.47656
80/80 [============ - 1s 6ms/step - loss: 53212.5117 - mae: 14
8.0289 - val loss: 60384.0117 - val mae: 153.1849
Epoch 31/350
```

```
Epoch 31: val_loss did not improve from 60175.47656
80/80 [============= ] - 0s 6ms/step - loss: 53425.9336 - mae: 15
1.5669 - val_loss: 63216.4961 - val_mae: 153.0728
Epoch 32/350
Epoch 32: val_loss improved from 60175.47656 to 59070.60938, saving model to regre
ssor weights-32-59070.609.hdf5
5.4349 - val_loss: 59070.6094 - val_mae: 149.4662
Epoch 33/350
Epoch 33: val loss improved from 59070.60938 to 57211.31641, saving model to regre
ssor weights-33-57211.316.hdf5
80/80 [============ - 1s 7ms/step - loss: 52556.0117 - mae: 14
6.1620 - val_loss: 57211.3164 - val_mae: 151.7694
Epoch 34/350
Epoch 34: val_loss improved from 57211.31641 to 55916.24219, saving model to regre
ssor weights-34-55916.242.hdf5
80/80 [============ - 1s 7ms/step - loss: 50740.8047 - mae: 14
5.6187 - val_loss: 55916.2422 - val_mae: 146.0040
Epoch 35/350
Epoch 35: val_loss improved from 55916.24219 to 55494.91016, saving model to regre
ssor_weights-35-55494.910.hdf5
80/80 [===========] - 1s 8ms/step - loss: 49035.7266 - mae: 13
9.0995 - val loss: 55494.9102 - val mae: 150.3178
Epoch 36/350
Epoch 36: val_loss did not improve from 55494.91016
4.4516 - val_loss: 55600.7422 - val_mae: 145.0783
Epoch 37/350
Epoch 37: val loss did not improve from 55494.91016
80/80 [============ - 0s 6ms/step - loss: 49463.7031 - mae: 14
3.6192 - val loss: 55847.9961 - val mae: 151.4101
Epoch 38/350
Epoch 38: val_loss did not improve from 55494.91016
7.3727 - val loss: 59064.0117 - val mae: 158.6001
Epoch 39/350
Epoch 39: val_loss improved from 55494.91016 to 51103.87891, saving model to regre
ssor weights-39-51103.879.hdf5
80/80 [============ - 1s 7ms/step - loss: 48272.0234 - mae: 14
4.0294 - val_loss: 51103.8789 - val_mae: 140.4603
Epoch 40/350
Epoch 40: val loss did not improve from 51103.87891
80/80 [============ - 0s 6ms/step - loss: 44882.0273 - mae: 13
5.1453 - val_loss: 52868.4922 - val_mae: 152.3154
Epoch 41/350
```

```
Epoch 41: val_loss improved from 51103.87891 to 51037.70312, saving model to regre
ssor weights-41-51037.703.hdf5
6.3604 - val_loss: 51037.7031 - val_mae: 140.6616
Epoch 42/350
Epoch 42: val_loss did not improve from 51037.70312
80/80 [============= - 0s 6ms/step - loss: 44436.5781 - mae: 13
7.0025 - val_loss: 63806.0312 - val_mae: 170.2654
Epoch 43/350
80/80 [===========] - ETA: 0s - loss: 44605.5000 - mae: 137.349
Epoch 43: val_loss improved from 51037.70312 to 49520.31641, saving model to regre
ssor_weights-43-49520.316.hdf5
7.3495 - val_loss: 49520.3164 - val_mae: 148.0588
Epoch 44/350
Epoch 44: val_loss did not improve from 49520.31641
80/80 [============= ] - 0s 6ms/step - loss: 43578.8438 - mae: 13
5.0275 - val_loss: 50388.9766 - val_mae: 136.6909
Epoch 45/350
Epoch 45: val_loss improved from 49520.31641 to 49390.03906, saving model to regre
ssor_weights-45-49390.039.hdf5
80/80 [===========] - 1s 7ms/step - loss: 42490.4492 - mae: 13
4.6917 - val loss: 49390.0391 - val mae: 139.6277
Epoch 46/350
Epoch 46: val_loss improved from 49390.03906 to 44587.40625, saving model to regre
ssor_weights-46-44587.406.hdf5
1.4392 - val_loss: 44587.4062 - val_mae: 132.1325
Epoch 47/350
Epoch 47: val loss did not improve from 44587.40625
80/80 [============ - 1s 8ms/step - loss: 40232.4570 - mae: 12
9.2470 - val_loss: 46573.2969 - val_mae: 134.2410
Epoch 48/350
80/80 [============] - ETA: Os - loss: 40216.9844 - mae: 132.187
Epoch 48: val loss did not improve from 44587.40625
80/80 [============ - 0s 6ms/step - loss: 40216.9844 - mae: 13
2.1875 - val_loss: 50573.8711 - val_mae: 146.5023
Epoch 49/350
72/80 [===============>...] - ETA: 0s - loss: 38998.5898 - mae: 132.494
Epoch 49: val_loss did not improve from 44587.40625
80/80 [============= ] - Os 6ms/step - loss: 40933.5508 - mae: 13
3.9998 - val_loss: 54137.5742 - val_mae: 149.8275
Epoch 50/350
Epoch 50: val loss did not improve from 44587.40625
9.2709 - val_loss: 49777.6172 - val_mae: 151.7587
Epoch 51/350
```

```
Epoch 51: val_loss improved from 44587.40625 to 41769.60156, saving model to regre
ssor weights-51-41769.602.hdf5
80/80 [============= ] - 0s 6ms/step - loss: 38491.4297 - mae: 12
6.6937 - val_loss: 41769.6016 - val_mae: 128.0128
Epoch 52/350
Epoch 52: val_loss did not improve from 41769.60156
80/80 [============ - 1s 6ms/step - loss: 38737.5977 - mae: 13
0.2140 - val_loss: 42784.5820 - val_mae: 127.7155
Epoch 53/350
73/80 [===========>...] - ETA: 0s - loss: 37940.9688 - mae: 127.574
Epoch 53: val_loss improved from 41769.60156 to 41097.23438, saving model to regre
ssor_weights-53-41097.234.hdf5
7.5187 - val_loss: 41097.2344 - val_mae: 125.1445
Epoch 54/350
Epoch 54: val_loss improved from 41097.23438 to 39291.15234, saving model to regre
ssor weights-54-39291.152.hdf5
1.8090 - val_loss: 39291.1523 - val_mae: 125.9417
Epoch 55/350
Epoch 55: val_loss did not improve from 39291.15234
80/80 [===========] - 1s 7ms/step - loss: 34271.1289 - mae: 11
8.7541 - val_loss: 40653.0586 - val_mae: 125.8112
Epoch 56/350
Epoch 56: val_loss improved from 39291.15234 to 37378.65625, saving model to regre
ssor_weights-56-37378.656.hdf5
1.4540 - val_loss: 37378.6562 - val_mae: 123.6144
Epoch 57/350
Epoch 57: val loss did not improve from 37378.65625
0.7084 - val_loss: 37508.1094 - val_mae: 121.7487
Epoch 58/350
Epoch 58: val loss did not improve from 37378.65625
80/80 [============ - 0s 6ms/step - loss: 32203.4570 - mae: 11
5.7546 - val loss: 37457.8008 - val mae: 120.8661
Epoch 59/350
Epoch 59: val_loss did not improve from 37378.65625
0.2159 - val_loss: 38607.3789 - val_mae: 128.3577
Epoch 60/350
Epoch 60: val loss did not improve from 37378.65625
80/80 [============= - 0s 6ms/step - loss: 33639.1406 - mae: 12
0.9017 - val_loss: 38004.1875 - val_mae: 123.8089
Epoch 61/350
```

```
Epoch 61: val_loss did not improve from 37378.65625
80/80 [============= ] - 0s 6ms/step - loss: 31624.6816 - mae: 11
6.4993 - val_loss: 37844.2148 - val_mae: 127.0789
Epoch 62/350
Epoch 62: val_loss did not improve from 37378.65625
5.6470 - val_loss: 43584.9766 - val_mae: 140.4506
Epoch 63/350
Epoch 63: val loss improved from 37378.65625 to 35711.28516, saving model to regre
ssor weights-63-35711.285.hdf5
4.1770 - val_loss: 35711.2852 - val_mae: 127.3563
Epoch 64/350
Epoch 64: val_loss improved from 35711.28516 to 34465.57031, saving model to regre
ssor weights-64-34465.570.hdf5
80/80 [============= - 1s 7ms/step - loss: 29441.0801 - mae: 11
2.9539 - val_loss: 34465.5703 - val_mae: 117.4049
Epoch 65/350
Epoch 65: val_loss improved from 34465.57031 to 33742.07422, saving model to regre
ssor_weights-65-33742.074.hdf5
80/80 [===========] - 1s 7ms/step - loss: 31821.1426 - mae: 12
0.0586 - val loss: 33742.0742 - val mae: 121.1355
Epoch 66/350
Epoch 66: val_loss did not improve from 33742.07422
9.3800 - val_loss: 40226.7578 - val_mae: 144.7208
Epoch 67/350
Epoch 67: val loss improved from 33742.07422 to 33400.12500, saving model to regre
ssor weights-67-33400.125.hdf5
80/80 [============ - 1s 7ms/step - loss: 28671.8945 - mae: 11
1.7985 - val_loss: 33400.1250 - val_mae: 116.2635
Epoch 68/350
Epoch 68: val loss improved from 33400.12500 to 30546.83398, saving model to regre
ssor weights-68-30546.834.hdf5
80/80 [============ - 0s 6ms/step - loss: 27376.2129 - mae: 10
8.7413 - val_loss: 30546.8340 - val_mae: 110.5134
Epoch 69: val loss did not improve from 30546.83398
6.5619 - val_loss: 30632.1914 - val_mae: 109.4804
Epoch 70/350
Epoch 70: val loss improved from 30546.83398 to 29602.58594, saving model to regre
ssor_weights-70-29602.586.hdf5
```

```
9.9097 - val_loss: 29602.5859 - val_mae: 111.6204
Epoch 71/350
Epoch 71: val_loss did not improve from 29602.58594
2.5033 - val_loss: 31669.2891 - val_mae: 117.3014
Epoch 72/350
Epoch 72: val_loss did not improve from 29602.58594
5.6255 - val_loss: 32045.2109 - val_mae: 113.6184
Epoch 73/350
Epoch 73: val_loss improved from 29602.58594 to 28971.80859, saving model to regre
ssor_weights-73-28971.809.hdf5
0.1673 - val_loss: 28971.8086 - val_mae: 108.6653
Epoch 74/350
Epoch 74: val loss improved from 28971.80859 to 27943.34180, saving model to regre
ssor weights-74-27943.342.hdf5
2.8468 - val_loss: 27943.3418 - val_mae: 106.6486
Epoch 75/350
Epoch 75: val_loss did not improve from 27943.34180
2.2744 - val_loss: 30692.7695 - val_mae: 112.6774
Epoch 76/350
Epoch 76: val_loss did not improve from 27943.34180
2.2353 - val_loss: 40353.4180 - val_mae: 142.1416
Epoch 77/350
Epoch 77: val loss did not improve from 27943.34180
80/80 [============ - 1s 6ms/step - loss: 24277.8965 - mae: 10
3.4819 - val loss: 28057.7109 - val mae: 113.3377
Epoch 78/350
74/80 [===============>...] - ETA: 0s - loss: 22703.7031 - mae: 98.7930
Epoch 78: val loss did not improve from 27943.34180
80/80 [===========] - 0s 6ms/step - loss: 21865.9844 - mae: 97.
2604 - val loss: 29270.0957 - val mae: 109.9065
Epoch 79/350
Epoch 79: val loss did not improve from 27943.34180
80/80 [============] - 0s 6ms/step - loss: 24360.2676 - mae: 10
4.4379 - val_loss: 28508.7383 - val_mae: 103.6913
Epoch 80/350
Epoch 80: val loss did not improve from 27943.34180
5834 - val_loss: 29065.0996 - val_mae: 116.3375
Epoch 81/350
Epoch 81: val_loss improved from 27943.34180 to 26783.65234, saving model to regre
ssor_weights-81-26783.652.hdf5
```

```
80/80 [============] - 1s 7ms/step - loss: 21438.3125 - mae: 96.
7243 - val_loss: 26783.6523 - val_mae: 100.1353
Epoch 82/350
Epoch 82: val_loss improved from 26783.65234 to 25962.27734, saving model to regre
ssor weights-82-25962.277.hdf5
80/80 [============] - 1s 7ms/step - loss: 21649.7188 - mae: 97.
1768 - val_loss: 25962.2773 - val_mae: 102.5116
Epoch 83/350
Epoch 83: val_loss did not improve from 25962.27734
80/80 [===========] - 0s 6ms/step - loss: 20900.3867 - mae: 96.
0766 - val_loss: 25980.2793 - val_mae: 108.6397
Epoch 84/350
Epoch 84: val_loss improved from 25962.27734 to 23760.43750, saving model to regre
ssor_weights-84-23760.438.hdf5
80/80 [============= ] - 1s 7ms/step - loss: 19500.0098 - mae: 89.
9133 - val_loss: 23760.4375 - val_mae: 100.7198
Epoch 85/350
Epoch 85: val_loss did not improve from 23760.43750
80/80 [===========] - 1s 7ms/step - loss: 20369.9805 - mae: 94.
5012 - val_loss: 27073.0605 - val_mae: 104.5292
Epoch 86/350
Epoch 86: val loss did not improve from 23760.43750
80/80 [============] - 0s 6ms/step - loss: 19334.7227 - mae: 91.
5152 - val_loss: 25395.2227 - val_mae: 100.9275
Epoch 87/350
Epoch 87: val loss did not improve from 23760.43750
1.4962 - val_loss: 25159.5684 - val_mae: 106.3865
Epoch 88/350
Epoch 88: val_loss did not improve from 23760.43750
80/80 [===========] - 0s 6ms/step - loss: 18794.4629 - mae: 90.
9835 - val loss: 24465.6523 - val mae: 97.1110
Epoch 89/350
Epoch 89: val loss improved from 23760.43750 to 22440.09375, saving model to regre
ssor weights-89-22440.094.hdf5
80/80 [===========] - 0s 6ms/step - loss: 19673.1504 - mae: 92.
7391 - val_loss: 22440.0938 - val_mae: 99.0639
Epoch 90/350
Epoch 90: val loss did not improve from 22440.09375
80/80 [===========] - 0s 6ms/step - loss: 19624.4258 - mae: 92.
8096 - val loss: 24077.7949 - val mae: 107.4695
Epoch 91/350
Epoch 91: val_loss improved from 22440.09375 to 21445.29883, saving model to regre
ssor weights-91-21445.299.hdf5
80/80 [===========] - 1s 7ms/step - loss: 17990.2422 - mae: 88.
7073 - val_loss: 21445.2988 - val_mae: 90.8661
Epoch 92/350
Epoch 92: val_loss did not improve from 21445.29883
80/80 [=========== ] - 0s 6ms/step - loss: 18054.1680 - mae: 89.
2032 - val loss: 23727.3145 - val mae: 98.5058
Epoch 93/350
```

```
Epoch 93: val loss did not improve from 21445.29883
80/80 [===========] - 0s 6ms/step - loss: 19160.7695 - mae: 93.
1055 - val_loss: 22581.1953 - val_mae: 102.1993
Epoch 94/350
Epoch 94: val_loss improved from 21445.29883 to 19943.82422, saving model to regre
ssor weights-94-19943.824.hdf5
80/80 [===========] - 1s 7ms/step - loss: 17087.8496 - mae: 85.
2673 - val_loss: 19943.8242 - val_mae: 88.9435
Epoch 95/350
Epoch 95: val_loss did not improve from 19943.82422
80/80 [===========] - 0s 6ms/step - loss: 17880.4922 - mae: 89.
4112 - val_loss: 22450.0117 - val_mae: 93.5237
Epoch 96/350
Epoch 96: val_loss did not improve from 19943.82422
80/80 [============] - 0s 6ms/step - loss: 16528.8418 - mae: 83.
9219 - val_loss: 20874.6641 - val_mae: 97.9785
Epoch 97/350
Epoch 97: val_loss improved from 19943.82422 to 18113.40625, saving model to regre
ssor weights-97-18113.406.hdf5
80/80 [===========] - 1s 6ms/step - loss: 15812.5010 - mae: 83.
4228 - val_loss: 18113.4062 - val_mae: 87.0239
Epoch 98/350
Epoch 98: val_loss did not improve from 18113.40625
80/80 [============] - 0s 6ms/step - loss: 15571.8154 - mae: 83.
4928 - val_loss: 22035.4043 - val_mae: 90.9299
Epoch 99/350
Epoch 99: val loss did not improve from 18113.40625
80/80 [============] - 0s 6ms/step - loss: 15870.6953 - mae: 84.
0451 - val_loss: 18400.8809 - val_mae: 84.9484
Epoch 100/350
74/80 [===============>...] - ETA: 0s - loss: 15002.8828 - mae: 78.7864
Epoch 100: val_loss did not improve from 18113.40625
80/80 [============] - 1s 8ms/step - loss: 14825.1670 - mae: 78.
9279 - val loss: 19257.3320 - val mae: 93.1779
Epoch 101/350
Epoch 101: val loss did not improve from 18113.40625
80/80 [=========== ] - 0s 6ms/step - loss: 15158.4902 - mae: 81.
7898 - val_loss: 18641.0820 - val_mae: 90.5377
Epoch 102/350
Epoch 102: val_loss did not improve from 18113.40625
80/80 [===========] - 1s 7ms/step - loss: 15455.6592 - mae: 82.
3160 - val loss: 20893.6250 - val mae: 102.4535
Epoch 103/350
Epoch 103: val_loss improved from 18113.40625 to 18046.66797, saving model to regr
essor_weights-103-18046.668.hdf5
8042 - val_loss: 18046.6680 - val_mae: 88.5354
Epoch 104/350
Epoch 104: val loss did not improve from 18046.66797
80/80 [===========] - 1s 6ms/step - loss: 13810.0479 - mae: 77.
4373 - val_loss: 18150.2246 - val_mae: 91.0318
Epoch 105/350
Epoch 105: val_loss improved from 18046.66797 to 16646.83984, saving model to regr
```

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essor weights-105-16646.840.hdf5
80/80 [============] - 1s 7ms/step - loss: 14077.2666 - mae: 79.
8074 - val_loss: 16646.8398 - val_mae: 83.4347
Epoch 106/350
Epoch 106: val loss did not improve from 16646.83984
80/80 [===========] - 1s 9ms/step - loss: 13814.4014 - mae: 77.
6235 - val_loss: 17032.8965 - val_mae: 88.2494
Epoch 107/350
Epoch 107: val_loss improved from 16646.83984 to 16391.48047, saving model to regr
essor_weights-107-16391.480.hdf5
5.3006 - val_loss: 16391.4805 - val_mae: 86.1338
Epoch 108/350
Epoch 108: val_loss improved from 16391.48047 to 15513.94434, saving model to regr
essor_weights-108-15513.944.hdf5
80/80 [============] - 1s 8ms/step - loss: 12758.5537 - mae: 75.
0651 - val_loss: 15513.9443 - val_mae: 77.6651
Epoch 109/350
Epoch 109: val loss did not improve from 15513.94434
80/80 [===========] - 1s 7ms/step - loss: 14147.4482 - mae: 81.
7555 - val_loss: 16233.7324 - val_mae: 85.2244
Epoch 110/350
Epoch 110: val_loss did not improve from 15513.94434
80/80 [============] - 1s 7ms/step - loss: 12877.4268 - mae: 75.
5250 - val_loss: 15647.2529 - val_mae: 80.7373
Epoch 111/350
Epoch 111: val loss improved from 15513.94434 to 14951.35449, saving model to regr
essor_weights-111-14951.354.hdf5
80/80 [============] - 1s 7ms/step - loss: 12529.3135 - mae: 74.
4971 - val_loss: 14951.3545 - val_mae: 78.4301
Epoch 112/350
Epoch 112: val_loss did not improve from 14951.35449
80/80 [===========] - 0s 6ms/step - loss: 12000.2520 - mae: 72.
2228 - val_loss: 18106.1113 - val_mae: 90.4650
Epoch 113/350
Epoch 113: val loss did not improve from 14951.35449
80/80 [============] - 0s 6ms/step - loss: 11637.1846 - mae: 71.
3537 - val_loss: 18621.3262 - val_mae: 101.4959
Epoch 114/350
74/80 [=============>...] - ETA: 0s - loss: 13537.2041 - mae: 80.4310
Epoch 114: val loss improved from 14951.35449 to 14774.61328, saving model to regr
essor weights-114-14774.613.hdf5
80/80 [===========] - 1s 8ms/step - loss: 13375.4072 - mae: 79.
8694 - val loss: 14774.6133 - val mae: 79.7950
Epoch 115: val_loss improved from 14774.61328 to 14285.47949, saving model to regr
essor weights-115-14285.479.hdf5
80/80 [============] - 1s 7ms/step - loss: 11295.2275 - mae: 70.
4310 - val loss: 14285.4795 - val mae: 74.8508
Epoch 116/350
Epoch 116: val loss did not improve from 14285.47949
80/80 [=========== ] - 0s 6ms/step - loss: 11902.1064 - mae: 73.
6035 - val_loss: 19612.7461 - val_mae: 98.2696
Epoch 117/350
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Epoch 117: val_loss improved from 14285.47949 to 12593.24121, saving model to regr
essor weights-117-12593.241.hdf5
80/80 [===========] - 1s 7ms/step - loss: 12757.3105 - mae: 77.
1737 - val_loss: 12593.2412 - val_mae: 73.9296
Epoch 118/350
Epoch 118: val_loss did not improve from 12593.24121
80/80 [============] - 1s 6ms/step - loss: 10934.4248 - mae: 70.
1012 - val_loss: 13009.9082 - val_mae: 73.4415
Epoch 119/350
Epoch 119: val_loss did not improve from 12593.24121
80/80 [===========] - 0s 6ms/step - loss: 10741.0000 - mae: 69.
6509 - val loss: 15815.4160 - val mae: 84.5406
Epoch 120/350
Epoch 120: val_loss did not improve from 12593.24121
80/80 [============] - 1s 6ms/step - loss: 11355.6426 - mae: 72.
1583 - val_loss: 13597.8740 - val_mae: 76.6830
Epoch 121/350
Epoch 121: val_loss improved from 12593.24121 to 12177.25977, saving model to regr
essor weights-121-12177.260.hdf5
427 - val_loss: 12177.2598 - val_mae: 72.8449
Epoch 122/350
Epoch 122: val_loss did not improve from 12177.25977
494 - val_loss: 14964.4590 - val_mae: 80.4405
Epoch 123/350
Epoch 123: val_loss did not improve from 12177.25977
259 - val_loss: 12430.2051 - val_mae: 71.7505
Epoch 124/350
Epoch 124: val_loss improved from 12177.25977 to 11764.79297, saving model to regr
essor weights-124-11764.793.hdf5
442 - val_loss: 11764.7930 - val_mae: 73.6221
Epoch 125/350
Epoch 125: val loss did not improve from 11764.79297
80/80 [==========] - 0s 6ms/step - loss: 9455.8594 - mae: 65.6
869 - val_loss: 12432.2646 - val_mae: 71.4669
Epoch 126/350
Epoch 126: val loss did not improve from 11764.79297
80/80 [===========] - 1s 7ms/step - loss: 10375.6826 - mae: 70.
2125 - val loss: 13268.9922 - val mae: 71.5710
Epoch 127/350
71/80 [==========>:...] - ETA: 0s - loss: 9348.0088 - mae: 65.3578
Epoch 127: val_loss did not improve from 11764.79297
371 - val_loss: 13472.0391 - val_mae: 81.5763
Epoch 128/350
Epoch 128: val_loss improved from 11764.79297 to 11357.42871, saving model to regr
essor weights-128-11357.429.hdf5
920 - val_loss: 11357.4287 - val_mae: 72.4896
Epoch 129/350
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Epoch 129: val_loss did not improve from 11357.42871
894 - val_loss: 12015.7686 - val_mae: 67.0166
Epoch 130/350
69/80 [===========>.....] - ETA: 0s - loss: 9030.0283 - mae: 63.8336
Epoch 130: val_loss improved from 11357.42871 to 10430.10254, saving model to regr
essor_weights-130-10430.103.hdf5
676 - val_loss: 10430.1025 - val_mae: 62.9999
Epoch 131/350
Epoch 131: val_loss did not improve from 10430.10254
932 - val loss: 11469.9600 - val mae: 75.6631
Epoch 132/350
Epoch 132: val_loss did not improve from 10430.10254
175 - val_loss: 14715.6104 - val_mae: 83.0952
Epoch 133/350
Epoch 133: val loss did not improve from 10430.10254
388 - val_loss: 15825.4424 - val_mae: 87.4919
Epoch 134/350
Epoch 134: val_loss improved from 10430.10254 to 9471.70117, saving model to regre
ssor_weights-134-9471.701.hdf5
982 - val_loss: 9471.7012 - val_mae: 66.7023
Epoch 135/350
Epoch 135: val_loss did not improve from 9471.70117
010 - val_loss: 14160.2148 - val_mae: 93.1612
Epoch 136/350
Epoch 136: val_loss did not improve from 9471.70117
142 - val loss: 9494.5049 - val mae: 62.6239
Epoch 137/350
Epoch 137: val loss did not improve from 9471.70117
80/80 [============ ] - 1s 6ms/step - loss: 8126.2402 - mae: 62.4
721 - val_loss: 10439.9131 - val_mae: 73.1618
Epoch 138/350
Epoch 138: val loss did not improve from 9471.70117
182 - val loss: 10436.8252 - val mae: 70.2133
Epoch 139/350
Epoch 139: val_loss improved from 9471.70117 to 9040.08691, saving model to regres
sor weights-139-9040.087.hdf5
846 - val_loss: 9040.0869 - val_mae: 60.6733
Epoch 140/350
Epoch 140: val_loss did not improve from 9040.08691
148 - val loss: 9077.2988 - val mae: 60.1694
Epoch 141/350
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Epoch 141: val loss did not improve from 9040.08691
395 - val_loss: 9419.3594 - val_mae: 60.3840
Epoch 142/350
Epoch 142: val_loss improved from 9040.08691 to 8968.68359, saving model to regres
sor weights-142-8968.684.hdf5
80/80 [===========] - 1s 7ms/step - loss: 7109.7583 - mae: 57.9
478 - val_loss: 8968.6836 - val_mae: 63.6573
Epoch 143/350
Epoch 143: val_loss improved from 8968.68359 to 8058.03662, saving model to regres
sor weights-143-8058.037.hdf5
80/80 [===========] - 1s 10ms/step - loss: 7297.2925 - mae: 59.
5085 - val loss: 8058.0366 - val mae: 57.6695
Epoch 144/350
Epoch 144: val_loss improved from 8058.03662 to 7935.68506, saving model to regres
sor weights-144-7935.685.hdf5
80/80 [===========] - 1s 8ms/step - loss: 6977.5981 - mae: 58.4
788 - val_loss: 7935.6851 - val_mae: 57.9420
Epoch 145/350
Epoch 145: val loss did not improve from 7935.68506
384 - val_loss: 13015.5410 - val_mae: 83.9599
Epoch 146/350
Epoch 146: val_loss did not improve from 7935.68506
910 - val_loss: 8962.5303 - val_mae: 61.1287
Epoch 147/350
Epoch 147: val_loss improved from 7935.68506 to 7850.60498, saving model to regres
sor weights-147-7850.605.hdf5
045 - val_loss: 7850.6050 - val_mae: 54.1756
Epoch 148/350
Epoch 148: val loss improved from 7850.60498 to 7751.21680, saving model to regres
sor weights-148-7751.217.hdf5
015 - val loss: 7751.2168 - val mae: 54.9803
Epoch 149/350
Epoch 149: val_loss improved from 7751.21680 to 7271.13574, saving model to regres
sor weights-149-7271.136.hdf5
887 - val loss: 7271.1357 - val mae: 57.7265
Epoch 150/350
Epoch 150: val loss did not improve from 7271.13574
166 - val_loss: 8243.9639 - val_mae: 60.3656
Epoch 151/350
Epoch 151: val_loss did not improve from 7271.13574
476 - val_loss: 7570.1113 - val_mae: 59.2664
Epoch 152/350
Epoch 152: val_loss improved from 7271.13574 to 6959.09717, saving model to regres
sor weights-152-6959.097.hdf5
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858 - val_loss: 6959.0972 - val_mae: 52.5045
Epoch 153/350
Epoch 153: val_loss did not improve from 6959.09717
084 - val loss: 9237.9971 - val mae: 61.6113
Epoch 154/350
Epoch 154: val_loss did not improve from 6959.09717
799 - val_loss: 7159.2778 - val_mae: 53.4091
Epoch 155/350
Epoch 155: val_loss did not improve from 6959.09717
317 - val_loss: 7609.1367 - val_mae: 56.5391
Epoch 156/350
Epoch 156: val_loss did not improve from 6959.09717
963 - val_loss: 7523.2573 - val_mae: 57.3337
Epoch 157/350
Epoch 157: val loss did not improve from 6959.09717
80/80 [===========] - 0s 6ms/step - loss: 5051.3257 - mae: 47.7
979 - val_loss: 8156.5288 - val_mae: 64.9167
Epoch 158/350
Epoch 158: val_loss did not improve from 6959.09717
860 - val_loss: 8988.5469 - val_mae: 72.9170
Epoch 159/350
Epoch 159: val_loss improved from 6959.09717 to 6320.23096, saving model to regres
sor weights-159-6320.231.hdf5
314 - val_loss: 6320.2310 - val_mae: 51.8063
Epoch 160/350
Epoch 160: val loss did not improve from 6320.23096
691 - val loss: 6495.4795 - val mae: 50.5248
Epoch 161/350
Epoch 161: val_loss did not improve from 6320.23096
805 - val_loss: 6398.7827 - val_mae: 54.7753
Epoch 162/350
Epoch 162: val loss did not improve from 6320.23096
784 - val loss: 6788.3003 - val mae: 52.2975
Epoch 163: val_loss improved from 6320.23096 to 6080.71924, saving model to regres
sor weights-163-6080.719.hdf5
714 - val loss: 6080.7192 - val mae: 49.4160
Epoch 164/350
Epoch 164: val loss did not improve from 6080.71924
611 - val_loss: 6434.7173 - val_mae: 51.5376
Epoch 165/350
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Epoch 165: val_loss did not improve from 6080.71924
80/80 [===========] - 1s 7ms/step - loss: 4542.1182 - mae: 46.6
905 - val_loss: 6317.1621 - val_mae: 50.7033
Epoch 166/350
Epoch 166: val_loss did not improve from 6080.71924
987 - val_loss: 6410.4800 - val_mae: 48.7216
Epoch 167/350
Epoch 167: val_loss improved from 6080.71924 to 5660.19238, saving model to regres
sor weights-167-5660.192.hdf5
678 - val loss: 5660.1924 - val mae: 50.3449
Epoch 168/350
Epoch 168: val_loss improved from 5660.19238 to 5310.00488, saving model to regres
sor weights-168-5310.005.hdf5
80/80 [===========] - 1s 7ms/step - loss: 4738.7520 - mae: 48.0
018 - val_loss: 5310.0049 - val_mae: 47.6777
Epoch 169/350
Epoch 169: val loss did not improve from 5310.00488
528 - val_loss: 7744.2495 - val_mae: 63.1517
Epoch 170/350
Epoch 170: val_loss improved from 5310.00488 to 5289.45410, saving model to regres
sor_weights-170-5289.454.hdf5
80/80 [============] - 1s 10ms/step - loss: 4291.6094 - mae: 45.
3898 - val_loss: 5289.4541 - val_mae: 48.0103
Epoch 171/350
Epoch 171: val_loss improved from 5289.45410 to 5207.59814, saving model to regres
sor weights-171-5207.598.hdf5
556 - val_loss: 5207.5981 - val_mae: 46.2112
Epoch 172/350
Epoch 172: val loss did not improve from 5207.59814
718 - val_loss: 5573.1401 - val_mae: 45.2715
Epoch 173/350
Epoch 173: val_loss did not improve from 5207.59814
327 - val_loss: 8723.7998 - val_mae: 67.9103
Epoch 174/350
Epoch 174: val_loss improved from 5207.59814 to 4914.49463, saving model to regres
sor weights-174-4914.495.hdf5
804 - val_loss: 4914.4946 - val_mae: 47.0734
Epoch 175/350
Epoch 175: val_loss did not improve from 4914.49463
654 - val_loss: 5591.4126 - val_mae: 47.6058
Epoch 176/350
Epoch 176: val loss did not improve from 4914.49463
80/80 [===========] - 0s 6ms/step - loss: 3954.8145 - mae: 43.9
502 - val_loss: 5507.6353 - val_mae: 49.1970
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Epoch 177/350
Epoch 177: val_loss improved from 4914.49463 to 4661.64307, saving model to regres
sor weights-177-4661.643.hdf5
722 - val loss: 4661.6431 - val mae: 41.9144
Epoch 178/350
Epoch 178: val_loss did not improve from 4661.64307
191 - val_loss: 5605.7954 - val_mae: 47.3167
Epoch 179/350
Epoch 179: val_loss did not improve from 4661.64307
708 - val_loss: 5402.2407 - val_mae: 53.4220
Epoch 180/350
Epoch 180: val_loss did not improve from 4661.64307
853 - val_loss: 5232.9907 - val_mae: 47.7159
Epoch 181/350
Epoch 181: val loss did not improve from 4661.64307
657 - val_loss: 5141.5864 - val_mae: 44.6625
Epoch 182/350
Epoch 182: val_loss did not improve from 4661.64307
983 - val_loss: 6810.6094 - val_mae: 49.6103
Epoch 183/350
Epoch 183: val_loss did not improve from 4661.64307
558 - val_loss: 5451.4756 - val_mae: 47.5943
Epoch 184/350
Epoch 184: val_loss did not improve from 4661.64307
330 - val loss: 5185.5762 - val mae: 48.9029
Epoch 185/350
Epoch 185: val loss did not improve from 4661.64307
727 - val_loss: 5392.1904 - val_mae: 50.8788
Epoch 186/350
Epoch 186: val loss improved from 4661.64307 to 3881.43945, saving model to regres
sor weights-186-3881.439.hdf5
923 - val loss: 3881.4395 - val mae: 39.1128
Epoch 187/350
80/80 [============] - ETA: 0s - loss: 3066.5095 - mae: 37.7640
Epoch 187: val_loss did not improve from 3881.43945
640 - val_loss: 4537.8813 - val_mae: 42.5737
Epoch 188/350
Epoch 188: val loss did not improve from 3881.43945
143 - val loss: 4271.4751 - val mae: 39.2825
Epoch 189/350
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Epoch 189: val loss did not improve from 3881.43945
978 - val_loss: 4131.4336 - val_mae: 39.8121
Epoch 190/350
Epoch 190: val_loss improved from 3881.43945 to 3754.92578, saving model to regres
sor weights-190-3754.926.hdf5
208 - val_loss: 3754.9258 - val_mae: 39.1589
Epoch 191/350
Epoch 191: val_loss did not improve from 3754.92578
80/80 [===========] - 0s 6ms/step - loss: 2756.4299 - mae: 35.9
369 - val_loss: 4184.3970 - val_mae: 41.0970
Epoch 192/350
Epoch 192: val_loss improved from 3754.92578 to 3688.52637, saving model to regres
sor_weights-192-3688.526.hdf5
442 - val_loss: 3688.5264 - val_mae: 36.8771
Epoch 193/350
Epoch 193: val loss did not improve from 3688.52637
930 - val_loss: 5380.4185 - val_mae: 50.6281
Epoch 194/350
Epoch 194: val_loss did not improve from 3688.52637
534 - val_loss: 5023.4302 - val_mae: 42.7295
Epoch 195/350
Epoch 195: val loss improved from 3688.52637 to 3454.97070, saving model to regres
sor_weights-195-3454.971.hdf5
199 - val_loss: 3454.9707 - val_mae: 36.3142
Epoch 196/350
Epoch 196: val_loss did not improve from 3454.97070
971 - val loss: 3746.5615 - val mae: 38.1061
Epoch 197/350
Epoch 197: val loss did not improve from 3454.97070
773 - val_loss: 4898.0889 - val_mae: 43.2683
Epoch 198/350
Epoch 198: val loss did not improve from 3454.97070
782 - val loss: 4349.7964 - val mae: 46.8063
Epoch 199/350
Epoch 199: val_loss did not improve from 3454.97070
918 - val_loss: 4628.2505 - val_mae: 47.2891
Epoch 200/350
Epoch 200: val loss did not improve from 3454.97070
243 - val loss: 4308.9985 - val mae: 44.3341
Epoch 201/350
Epoch 201: val_loss did not improve from 3454.97070
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902 - val_loss: 3916.2097 - val_mae: 39.7325
Epoch 202/350
Epoch 202: val_loss did not improve from 3454.97070
910 - val_loss: 4301.1250 - val_mae: 44.5302
Epoch 203/350
Epoch 203: val_loss improved from 3454.97070 to 3111.08423, saving model to regres
sor_weights-203-3111.084.hdf5
236 - val_loss: 3111.0842 - val_mae: 37.2758
Epoch 204/350
Epoch 204: val_loss improved from 3111.08423 to 2988.68555, saving model to regres
sor_weights-204-2988.686.hdf5
029 - val_loss: 2988.6855 - val_mae: 34.0675
Epoch 205/350
Epoch 205: val_loss did not improve from 2988.68555
231 - val_loss: 3571.8066 - val_mae: 37.9526
Epoch 206/350
Epoch 206: val_loss did not improve from 2988.68555
766 - val_loss: 3264.5273 - val_mae: 35.4158
Epoch 207/350
Epoch 207: val loss did not improve from 2988.68555
021 - val_loss: 3088.2354 - val_mae: 33.3363
Epoch 208/350
Epoch 208: val_loss improved from 2988.68555 to 2819.05811, saving model to regres
sor weights-208-2819.058.hdf5
835 - val loss: 2819.0581 - val mae: 34.0478
Epoch 209/350
Epoch 209: val loss did not improve from 2819.05811
066 - val_loss: 3028.4702 - val_mae: 36.0186
Epoch 210/350
Epoch 210: val_loss did not improve from 2819.05811
474 - val loss: 2939.5793 - val mae: 33.7234
Epoch 211/350
Epoch 211: val loss did not improve from 2819.05811
162 - val_loss: 3426.6318 - val_mae: 41.1121
Epoch 212/350
Epoch 212: val loss did not improve from 2819.05811
189 - val_loss: 3041.5764 - val_mae: 36.7259
Epoch 213/350
Epoch 213: val_loss did not improve from 2819.05811
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822 - val_loss: 3002.1975 - val_mae: 35.1730
Epoch 214/350
Epoch 214: val_loss did not improve from 2819.05811
154 - val loss: 3348.5144 - val mae: 35.7886
Epoch 215/350
Epoch 215: val_loss improved from 2819.05811 to 2643.35181, saving model to regres
sor weights-215-2643.352.hdf5
996 - val_loss: 2643.3518 - val_mae: 32.2646
Epoch 216/350
Epoch 216: val loss did not improve from 2643.35181
610 - val_loss: 3878.1887 - val_mae: 35.6599
Epoch 217/350
Epoch 217: val_loss did not improve from 2643.35181
237 - val_loss: 3956.2710 - val_mae: 47.1780
Epoch 218/350
Epoch 218: val loss did not improve from 2643.35181
740 - val_loss: 3459.6086 - val_mae: 41.1598
Epoch 219/350
Epoch 219: val_loss did not improve from 2643.35181
80/80 [============] - 0s 6ms/step - loss: 2220.6677 - mae: 32.9
062 - val_loss: 3110.4146 - val_mae: 40.4632
Epoch 220/350
Epoch 220: val_loss did not improve from 2643.35181
501 - val_loss: 3437.6040 - val_mae: 44.3097
Epoch 221/350
Epoch 221: val loss did not improve from 2643.35181
741 - val_loss: 5188.2559 - val_mae: 44.7384
Epoch 222/350
Epoch 222: val_loss improved from 2643.35181 to 2523.51562, saving model to regres
sor_weights-222-2523.516.hdf5
329 - val_loss: 2523.5156 - val_mae: 30.2176
Epoch 223/350
Epoch 223: val loss did not improve from 2523.51562
145 - val_loss: 2694.1750 - val_mae: 32.5845
Epoch 224/350
Epoch 224: val loss did not improve from 2523.51562
260 - val_loss: 3268.8093 - val_mae: 36.0295
Epoch 225/350
Epoch 225: val loss did not improve from 2523.51562
901 - val_loss: 5321.9473 - val_mae: 60.0554
Epoch 226/350
```

```
Epoch 226: val_loss improved from 2523.51562 to 2519.00439, saving model to regres
sor weights-226-2519.004.hdf5
242 - val_loss: 2519.0044 - val_mae: 30.9378
Epoch 227/350
Epoch 227: val_loss did not improve from 2519.00439
814 - val_loss: 3127.9724 - val_mae: 34.2370
Epoch 228/350
Epoch 228: val_loss did not improve from 2519.00439
682 - val loss: 3490.2454 - val mae: 41.2958
Epoch 229/350
Epoch 229: val_loss did not improve from 2519.00439
163 - val_loss: 3042.6367 - val_mae: 34.2681
Epoch 230/350
Epoch 230: val loss did not improve from 2519.00439
797 - val_loss: 3291.0681 - val_mae: 42.3369
Epoch 231/350
Epoch 231: val_loss improved from 2519.00439 to 2096.59448, saving model to regres
sor_weights-231-2096.594.hdf5
073 - val_loss: 2096.5945 - val_mae: 28.7356
Epoch 232/350
Epoch 232: val_loss did not improve from 2096.59448
609 - val_loss: 2586.7227 - val_mae: 27.1825
Epoch 233/350
Epoch 233: val_loss did not improve from 2096.59448
278 - val loss: 2617.2959 - val mae: 31.7901
Epoch 234/350
Epoch 234: val loss did not improve from 2096.59448
023 - val_loss: 3471.5122 - val_mae: 40.6674
Epoch 235/350
Epoch 235: val loss did not improve from 2096.59448
800 - val loss: 2808.7886 - val mae: 34.0271
Epoch 236/350
Epoch 236: val_loss did not improve from 2096.59448
576 - val_loss: 2433.1865 - val_mae: 28.4003
Epoch 237/350
Epoch 237: val loss did not improve from 2096.59448
80/80 [==========] - 0s 6ms/step - loss: 2433.2864 - mae: 35.4
028 - val_loss: 3873.7600 - val_mae: 41.0313
Epoch 238/350
Epoch 238: val_loss did not improve from 2096.59448
```

```
113 - val_loss: 2175.0325 - val_mae: 28.4992
Epoch 239/350
Epoch 239: val_loss did not improve from 2096.59448
415 - val_loss: 3473.6099 - val_mae: 37.0831
Epoch 240/350
Epoch 240: val_loss did not improve from 2096.59448
576 - val_loss: 3367.1953 - val_mae: 39.4846
Epoch 241/350
72/80 [===========>...] - ETA: 0s - loss: 2583.9443 - mae: 35.0272
Epoch 241: val loss did not improve from 2096.59448
084 - val_loss: 4830.7471 - val_mae: 54.0176
Epoch 242/350
Epoch 242: val_loss did not improve from 2096.59448
538 - val_loss: 2274.6584 - val_mae: 27.3587
Epoch 243/350
Epoch 243: val loss did not improve from 2096.59448
771 - val_loss: 2304.3813 - val_mae: 27.3491
Epoch 244/350
Epoch 244: val_loss did not improve from 2096.59448
416 - val_loss: 3303.2375 - val_mae: 42.7044
Epoch 245/350
Epoch 245: val_loss improved from 2096.59448 to 2057.43872, saving model to regres
sor weights-245-2057.439.hdf5
337 - val_loss: 2057.4387 - val_mae: 25.0275
Epoch 246/350
Epoch 246: val loss did not improve from 2057.43872
518 - val_loss: 2434.1387 - val_mae: 32.8980
Epoch 247/350
Epoch 247: val_loss did not improve from 2057.43872
515 - val_loss: 2580.7859 - val_mae: 36.9123
Epoch 248/350
Epoch 248: val_loss improved from 2057.43872 to 1982.47913, saving model to regres
sor weights-248-1982.479.hdf5
322 - val_loss: 1982.4791 - val_mae: 26.5948
Epoch 249/350
Epoch 249: val_loss did not improve from 1982.47913
755 - val_loss: 2073.0278 - val_mae: 24.9457
Epoch 250/350
Epoch 250: val loss did not improve from 1982.47913
064 - val_loss: 2012.5358 - val_mae: 27.3105
```

```
Epoch 251/350
Epoch 251: val_loss did not improve from 1982.47913
896 - val_loss: 2033.6134 - val_mae: 25.4881
Epoch 252/350
Epoch 252: val_loss did not improve from 1982.47913
956 - val_loss: 2460.5398 - val_mae: 27.0928
Epoch 253/350
Epoch 253: val_loss did not improve from 1982.47913
748 - val loss: 2409.9763 - val mae: 29.1957
Epoch 254/350
Epoch 254: val_loss did not improve from 1982.47913
656 - val_loss: 2935.6621 - val_mae: 31.6654
Epoch 255/350
Epoch 255: val_loss improved from 1982.47913 to 1696.10352, saving model to regres
sor weights-255-1696.104.hdf5
377 - val_loss: 1696.1035 - val_mae: 23.7757
Epoch 256/350
Epoch 256: val_loss did not improve from 1696.10352
185 - val_loss: 2647.0178 - val_mae: 28.4290
Epoch 257/350
Epoch 257: val_loss did not improve from 1696.10352
80/80 [===========] - 1s 6ms/step - loss: 1715.1554 - mae: 29.6
266 - val_loss: 1819.6597 - val_mae: 25.1108
Epoch 258/350
Epoch 258: val_loss did not improve from 1696.10352
637 - val loss: 2359.5876 - val mae: 31.0336
Epoch 259/350
Epoch 259: val loss did not improve from 1696.10352
725 - val_loss: 2400.2261 - val_mae: 32.0283
Epoch 260/350
Epoch 260: val loss did not improve from 1696.10352
779 - val_loss: 2051.7336 - val_mae: 28.1442
Epoch 261/350
Epoch 261: val_loss did not improve from 1696.10352
636 - val_loss: 1809.3799 - val_mae: 24.9268
Epoch 262/350
Epoch 262: val loss did not improve from 1696.10352
466 - val_loss: 2209.1636 - val_mae: 28.1076
Epoch 263/350
Epoch 263: val_loss did not improve from 1696.10352
```

```
096 - val_loss: 3138.9470 - val_mae: 43.3370
Epoch 264/350
Epoch 264: val_loss improved from 1696.10352 to 1643.50476, saving model to regres
sor weights-264-1643.505.hdf5
80/80 [===========] - 1s 6ms/step - loss: 1911.0604 - mae: 31.5
793 - val_loss: 1643.5048 - val_mae: 24.4946
Epoch 265/350
Epoch 265: val_loss did not improve from 1643.50476
006 - val_loss: 2183.2009 - val_mae: 31.2972
Epoch 266/350
Epoch 266: val loss did not improve from 1643.50476
959 - val_loss: 1810.5625 - val_mae: 23.3000
Epoch 267/350
Epoch 267: val_loss did not improve from 1643.50476
251 - val_loss: 2303.0388 - val_mae: 31.0063
Epoch 268/350
Epoch 268: val_loss did not improve from 1643.50476
571 - val_loss: 3268.6133 - val_mae: 35.8012
Epoch 269/350
Epoch 269: val_loss did not improve from 1643.50476
859 - val loss: 2413.2800 - val mae: 36.3211
Epoch 270/350
Epoch 270: val_loss did not improve from 1643.50476
291 - val_loss: 2245.0791 - val_mae: 27.8187
Epoch 271/350
Epoch 271: val loss improved from 1643.50476 to 1590.92688, saving model to regres
sor weights-271-1590.927.hdf5
269 - val loss: 1590.9269 - val mae: 23.0601
Epoch 272/350
Epoch 272: val loss did not improve from 1590.92688
214 - val loss: 2111.2578 - val mae: 32.7381
Epoch 273/350
Epoch 273: val loss did not improve from 1590.92688
491 - val_loss: 1762.0186 - val_mae: 24.9408
Epoch 274/350
Epoch 274: val_loss did not improve from 1590.92688
412 - val_loss: 1701.2856 - val_mae: 23.0397
Epoch 275/350
Epoch 275: val loss did not improve from 1590.92688
919 - val_loss: 2134.2285 - val_mae: 30.2530
```

```
Epoch 276/350
Epoch 276: val_loss did not improve from 1590.92688
914 - val_loss: 2666.6279 - val_mae: 39.0767
Epoch 277/350
Epoch 277: val_loss did not improve from 1590.92688
902 - val_loss: 1612.4176 - val_mae: 23.6817
Epoch 278/350
Epoch 278: val_loss did not improve from 1590.92688
134 - val loss: 2612.3879 - val mae: 37.7537
Epoch 279/350
Epoch 279: val_loss did not improve from 1590.92688
354 - val_loss: 2498.9521 - val_mae: 35.0809
Epoch 280/350
Epoch 280: val loss did not improve from 1590.92688
737 - val_loss: 1919.6487 - val_mae: 31.5343
Epoch 281/350
Epoch 281: val_loss did not improve from 1590.92688
311 - val_loss: 1953.9058 - val_mae: 24.2535
Epoch 282/350
Epoch 282: val loss did not improve from 1590.92688
80/80 [===========] - 1s 6ms/step - loss: 1513.0328 - mae: 26.9
294 - val_loss: 2385.4363 - val_mae: 29.4430
Epoch 283/350
Epoch 283: val_loss did not improve from 1590.92688
889 - val loss: 1946.3052 - val mae: 25.4209
Epoch 284/350
Epoch 284: val loss did not improve from 1590.92688
411 - val_loss: 2829.2354 - val_mae: 38.3190
Epoch 285/350
Epoch 285: val_loss improved from 1590.92688 to 1553.80261, saving model to regres
sor weights-285-1553.803.hdf5
212 - val_loss: 1553.8026 - val_mae: 26.2393
Epoch 286/350
Epoch 286: val_loss did not improve from 1553.80261
121 - val_loss: 3051.3696 - val_mae: 39.8702
Epoch 287/350
Epoch 287: val loss did not improve from 1553.80261
80/80 [===========] - 0s 6ms/step - loss: 1420.5562 - mae: 26.0
013 - val_loss: 1784.2847 - val_mae: 25.1036
Epoch 288/350
Epoch 288: val_loss did not improve from 1553.80261
```

```
052 - val_loss: 2087.4192 - val_mae: 28.7076
Epoch 289/350
Epoch 289: val_loss did not improve from 1553.80261
33 - val_loss: 1564.7828 - val_mae: 23.4798
Epoch 290/350
73/80 [===============>...] - ETA: 0s - loss: 965.2160 - mae: 21.7382
Epoch 290: val_loss did not improve from 1553.80261
46 - val_loss: 1925.3960 - val_mae: 29.5945
Epoch 291/350
Epoch 291: val loss improved from 1553.80261 to 1427.13879, saving model to regres
sor weights-291-1427.139.hdf5
908 - val_loss: 1427.1388 - val_mae: 20.9274
Epoch 292/350
Epoch 292: val_loss did not improve from 1427.13879
730 - val_loss: 1593.7515 - val_mae: 21.3512
Epoch 293/350
75/80 [===========>..] - ETA: 0s - loss: 1086.8768 - mae: 21.3361
Epoch 293: val_loss improved from 1427.13879 to 1399.32141, saving model to regres
sor weights-293-1399.321.hdf5
034 - val_loss: 1399.3214 - val_mae: 22.2057
Epoch 294/350
69/80 [=========>.....] - ETA: 0s - loss: 950.0401 - mae: 21.0296
Epoch 294: val loss did not improve from 1399.32141
05 - val_loss: 1970.9573 - val_mae: 25.6401
Epoch 295/350
Epoch 295: val_loss improved from 1399.32141 to 1376.69897, saving model to regres
sor weights-295-1376.699.hdf5
82 - val loss: 1376.6990 - val mae: 19.9245
Epoch 296/350
Epoch 296: val loss did not improve from 1376.69897
072 - val_loss: 3394.3674 - val_mae: 42.7881
Epoch 297/350
Epoch 297: val_loss did not improve from 1376.69897
336 - val loss: 1832.4775 - val mae: 29.3682
Epoch 298/350
Epoch 298: val_loss improved from 1376.69897 to 1327.80908, saving model to regres
sor_weights-298-1327.809.hdf5
419 - val_loss: 1327.8091 - val_mae: 20.8985
Epoch 299/350
Epoch 299: val loss did not improve from 1327.80908
05 - val_loss: 1650.2323 - val_mae: 22.7431
Epoch 300/350
Epoch 300: val_loss improved from 1327.80908 to 1288.02039, saving model to regres
```

```
sor weights-300-1288.020.hdf5
956 - val_loss: 1288.0204 - val_mae: 20.5095
Epoch 301/350
Epoch 301: val loss did not improve from 1288.02039
02 - val_loss: 1597.2150 - val_mae: 21.9652
Epoch 302/350
Epoch 302: val_loss did not improve from 1288.02039
936 - val_loss: 1945.5203 - val_mae: 31.6535
Epoch 303/350
Epoch 303: val loss did not improve from 1288.02039
190 - val_loss: 2238.6890 - val_mae: 33.5828
Epoch 304/350
Epoch 304: val_loss did not improve from 1288.02039
543 - val_loss: 2138.0803 - val_mae: 29.2141
Epoch 305/350
Epoch 305: val_loss did not improve from 1288.02039
86 - val_loss: 1522.5768 - val_mae: 21.5435
Epoch 306/350
Epoch 306: val_loss did not improve from 1288.02039
40 - val loss: 2459.5271 - val mae: 35.6487
Epoch 307/350
Epoch 307: val_loss did not improve from 1288.02039
28 - val_loss: 1410.4567 - val_mae: 20.5427
Epoch 308/350
Epoch 308: val loss did not improve from 1288.02039
84 - val_loss: 1473.5800 - val_mae: 20.3723
Epoch 309/350
Epoch 309: val_loss did not improve from 1288.02039
64 - val_loss: 1692.6864 - val_mae: 26.7021
Epoch 310/350
Epoch 310: val_loss did not improve from 1288.02039
657 - val_loss: 1387.7737 - val_mae: 21.9571
Epoch 311/350
Epoch 311: val loss did not improve from 1288.02039
091 - val_loss: 1932.0034 - val_mae: 30.6071
Epoch 312/350
Epoch 312: val_loss improved from 1288.02039 to 1233.58838, saving model to regres
sor weights-312-1233.588.hdf5
80/80 [==========] - 1s 7ms/step - loss: 1113.6960 - mae: 23.9
500 - val_loss: 1233.5884 - val_mae: 19.3448
```

```
Epoch 313/350
Epoch 313: val_loss did not improve from 1233.58838
28 - val_loss: 1284.9498 - val_mae: 19.6495
Epoch 314/350
Epoch 314: val_loss did not improve from 1233.58838
99 - val_loss: 1653.0955 - val_mae: 25.4327
Epoch 315/350
Epoch 315: val_loss did not improve from 1233.58838
258 - val loss: 1378.4463 - val mae: 19.5149
Epoch 316/350
Epoch 316: val_loss did not improve from 1233.58838
31 - val_loss: 2152.1265 - val_mae: 28.2337
Epoch 317/350
Epoch 317: val loss did not improve from 1233.58838
214 - val_loss: 1912.8048 - val_mae: 23.2829
Epoch 318/350
Epoch 318: val_loss improved from 1233.58838 to 1227.09900, saving model to regres
sor_weights-318-1227.099.hdf5
611 - val_loss: 1227.0990 - val_mae: 19.0070
Epoch 319/350
Epoch 319: val_loss did not improve from 1227.09900
954 - val_loss: 1429.8992 - val_mae: 22.5532
Epoch 320/350
Epoch 320: val_loss did not improve from 1227.09900
58 - val_loss: 1368.6864 - val_mae: 21.7286
Epoch 321/350
Epoch 321: val loss did not improve from 1227.09900
58 - val_loss: 1383.7961 - val_mae: 19.5260
Epoch 322/350
Epoch 322: val loss did not improve from 1227.09900
04 - val_loss: 1627.7123 - val_mae: 23.6866
Epoch 323/350
Epoch 323: val_loss did not improve from 1227.09900
53 - val_loss: 1264.4202 - val_mae: 17.5715
Epoch 324/350
Epoch 324: val loss did not improve from 1227.09900
27 - val_loss: 1305.3613 - val_mae: 18.4607
Epoch 325/350
Epoch 325: val_loss did not improve from 1227.09900
```

```
83 - val_loss: 1449.8442 - val_mae: 21.4595
Epoch 326/350
Epoch 326: val_loss did not improve from 1227.09900
83 - val_loss: 1529.8300 - val_mae: 24.3213
Epoch 327/350
75/80 [============>..] - ETA: 0s - loss: 810.6590 - mae: 20.0662
Epoch 327: val_loss did not improve from 1227.09900
69 - val_loss: 1707.6467 - val_mae: 24.4538
Epoch 328/350
Epoch 328: val loss did not improve from 1227.09900
92 - val_loss: 1257.5422 - val_mae: 21.1339
Epoch 329/350
Epoch 329: val_loss did not improve from 1227.09900
73 - val_loss: 1353.7592 - val_mae: 24.3721
Epoch 330/350
Epoch 330: val loss did not improve from 1227.09900
674 - val_loss: 1300.7876 - val_mae: 22.9265
Epoch 331/350
Epoch 331: val_loss did not improve from 1227.09900
764 - val loss: 1762.1349 - val mae: 20.7695
Epoch 332/350
Epoch 332: val_loss improved from 1227.09900 to 1180.59814, saving model to regres
sor weights-332-1180.598.hdf5
17 - val_loss: 1180.5981 - val_mae: 19.1362
Epoch 333/350
Epoch 333: val loss did not improve from 1180.59814
70 - val_loss: 1284.2356 - val_mae: 20.9421
Epoch 334/350
71/80 [===========>....] - ETA: 0s - loss: 725.6735 - mae: 19.2124
Epoch 334: val_loss did not improve from 1180.59814
79 - val_loss: 1561.0117 - val_mae: 20.3717
Epoch 335/350
Epoch 335: val_loss improved from 1180.59814 to 1168.22241, saving model to regres
sor weights-335-1168.222.hdf5
51 - val_loss: 1168.2224 - val_mae: 16.3420
Epoch 336/350
Epoch 336: val_loss did not improve from 1168.22241
70 - val_loss: 1295.0427 - val_mae: 23.1587
Epoch 337/350
Epoch 337: val loss did not improve from 1168.22241
15 - val_loss: 1225.1069 - val_mae: 23.0618
```

```
Epoch 338/350
Epoch 338: val_loss did not improve from 1168.22241
24 - val_loss: 1460.0798 - val_mae: 20.6670
Epoch 339/350
Epoch 339: val_loss did not improve from 1168.22241
529 - val_loss: 1267.9713 - val_mae: 22.4405
Epoch 340/350
Epoch 340: val_loss did not improve from 1168.22241
48 - val loss: 1668.0361 - val mae: 28.1297
Epoch 341/350
Epoch 341: val_loss did not improve from 1168.22241
80 - val_loss: 1474.1300 - val_mae: 25.4259
Epoch 342/350
Epoch 342: val loss did not improve from 1168.22241
446 - val_loss: 1637.4370 - val_mae: 20.2945
Epoch 343/350
Epoch 343: val_loss did not improve from 1168.22241
70 - val_loss: 1413.1656 - val_mae: 25.2506
Epoch 344/350
Epoch 344: val loss improved from 1168.22241 to 1109.91821, saving model to regres
sor_weights-344-1109.918.hdf5
12 - val_loss: 1109.9182 - val_mae: 18.9070
Epoch 345/350
Epoch 345: val_loss did not improve from 1109.91821
88 - val loss: 1355.1189 - val mae: 21.1794
Epoch 346/350
Epoch 346: val loss did not improve from 1109.91821
86 - val_loss: 1293.9854 - val_mae: 18.7964
Epoch 347/350
Epoch 347: val loss did not improve from 1109.91821
80 - val_loss: 1178.9469 - val_mae: 17.4579
Epoch 348/350
Epoch 348: val_loss improved from 1109.91821 to 1095.96777, saving model to regres
sor weights-348-1095.968.hdf5
51 - val_loss: 1095.9678 - val_mae: 16.2032
Epoch 349/350
Epoch 349: val_loss did not improve from 1095.96777
81 - val loss: 1121.0232 - val mae: 18.2806
Epoch 350/350
```

Построение графика потери

Если функция потерь на тренировочной выборке продолжает уменьшаться, в то время как на валидационной выборке начинает возрастать, это является признаком переобучения

```
In [31]: loss_function = regressor_history.history['loss']
    val_loss_function = regressor_history.history['val_loss']
    epochs = range(1, len(loss_function)+1)

    plt.title('Loss function (Train & Val Sets)')
    plt.plot(epochs, loss_function, label='Train Loss')
    plt.plot(epochs, val_loss_function, color='orange', label='Val Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss function')
    plt.legend()
    plt.show()
```



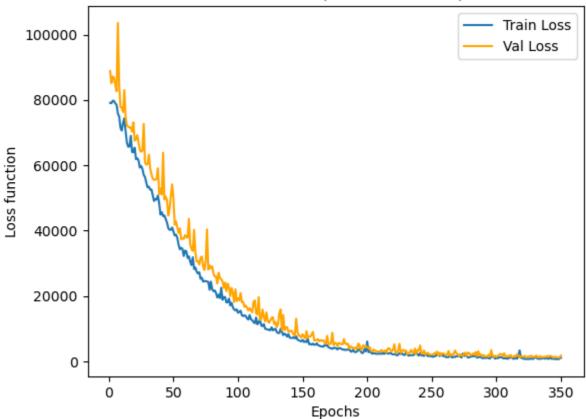


График изменения величины средней абсолютной ошибки (Mean Absolute Error, MAE) модели в процессе

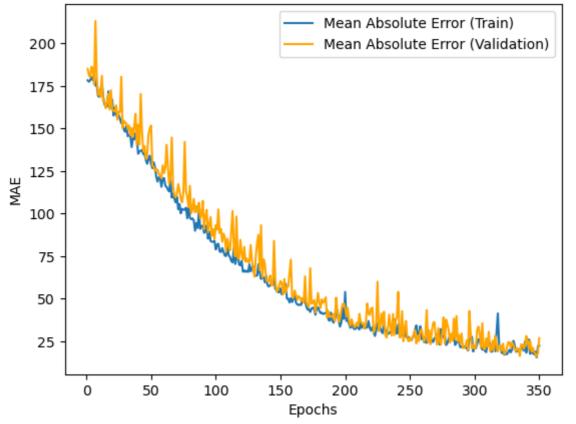
Две кривые: одна для обучающего набора данных ("Mean Absolute Error (Train)") и для валидационного набора данных ("Mean Absolute Error (Validation)"). Если на графике видно, что ошибка на обучающей выборке продолжает уменьшаться, в то время как ошибка на валидационной выборке начинает увеличиваться, это может свидетельствовать о переобучении модели, когда она хорошо обучается на

тренировочных данных, но плохо справляется с новыми, наблюдаемыми во время валидации данными.

```
In [32]: mae = regressor_history.history['mae']
    val_mae = regressor_history.history['val_mae']
    epochs = range(1, len(mae)+1)

plt.title('MAE (Train & Val Sets)')
    plt.plot(epochs, mae, label='Mean Absolute Error (Train)')
    plt.plot(epochs, val_mae, color='orange', label='Mean Absolute Error (Validation)')
    plt.xlabel('Epochs')
    plt.ylabel('MAE')
    plt.legend()
    plt.show()
```

MAE (Train & Val Sets)



results = regressor.evaluate(X_test, y_test)

Name: TOTALBTUCOL, Length: 995, dtype: int64

file:///C:/Users/vvadi/Desktop/DL13.html

688

15046

12806 2744

10903

5834

10531

1912

6279 3881

In [33]:

```
x test pattern = X test[2, :]
In [35]:
         y_pred = regressor.predict(x_test_pattern.reshape(1, -1))
         print(y_pred[0])
         [10929.391]
In [36]: original_features = min_max_scaler.inverse_transform(x_test_pattern.reshape(1, -1))
         original_features
         array([[3.00000000e+00, 7.00000000e+00, 2.10000000e+01, 4.61011000e+02,
Out[36]:
                 4.61000000e+02, 3.19867000e+03, 1.09138550e+04, 3.02000000e+02,
                 7.16000000e+03, 0.00000000e+00, 8.10162822e+03, 1.53600000e+03,
                 1.00000000e+00, 1.00000000e+00, 2.25600000e+03, 9.28817000e+02,
                 0.0000000e+00. 0.0000000e+00. 0.0000000e+00. 7.00000000e+01.
                 1.53600000e+03, 0.00000000e+00, 1.00000000e+00, 1.00000000e+00,
                 0.00000000e+00, 1.00000000e+00, 9.29000000e+02, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 2.09852000e+03,
                 7.16014700e+03, 0.00000000e+00, 0.00000000e+00, 4.00000000e+02,
                 2.25600000e+03, 1.00000000e+00, 3.02451000e+02, 1.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.0000000e+00, 0.00000000e+00,
                 4.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
                 4.00000000e+02, 1.93600000e+03, 1.53600000e+03, 0.00000000e+00,
                 0.00000000e+00, 1.00000000e+00, 0.00000000e+00, 5.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 2.00000000e+00,
                 0.00000000e+00, 5.34080000e+04, 1.00000000e+00, 0.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 3.62294000e+02, 2.51373900e+03,
                 8.57687100e+03, 6.00000000e+00, 1.00000000e+00, 0.00000000e+00,
                 0.00000000e+00, 2.19890000e+04, 0.00000000e+00, 0.00000000e+00,
                 2.00000000e+00, 0.00000000e+00, 3.00000000e+00, 1.00000000e+01,
                 0.00000000e+00, 0.00000000e+00, 1.00000000e+00, 0.00000000e+00,
                 5.00000000e+00, 0.00000000e+00, 0.00000000e+00, 2.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 6.44448900e+03,
                 0.0000000e+00, 3.6200000e+02, 0.00000000e+00, 0.00000000e+00,
                 1.98200000e+03, 2.19885820e+04, 1.56530000e+04, 5.34080000e+04,
                 0.0000000e+00, 0.0000000e+00, 0.0000000e+00, 0.0000000e+00,
                 0.00000000e+00, 6.50000000e+01, 1.00000000e+00, 8.57700000e+03,
                 5.00000000e+00, 2.01427000e+02, 2.01000000e+02, 6.00000000e+00,
                 0.00000000e+00, 0.00000000e+00, 5.00000000e+00, 1.39758200e+03]])
```

In [37]: x_test_pattern

```
Out[37]: array([0.5 , 0.66666667, 0.76923077, 0.05960983, 0.05964549,
                  0.0523986 , 0.05239854, 0.03259931, 0.017862 , 0.
                   0.17477496, 0.10244189, 0. , 0.1 , 0.11532785,
                  0.09676711, 0. , 0. , 0.
0.1055247 , 0. , 0. , 0.
0. , 0.06945639, 0. , 0.
                                                                     , 0.66666667,
                                                                     , 0.
                            , 0.15159057, 0.1515907 , 0. , 0.
87, 0.0682907 , 0.
                   0.
                  0.05270787, 0.0682907 , 0. , 0.22387924, 1.
                  0. , 0. , 0. , 0. , 0. , 0.42857143,

0. , 0. , 0. , 0. , 0. , 0. , 0.

0. , 0. , 0. , 0. , 0. , 0. , 0.

0. , 0. , 0. , 0. , 0. , 0.2 , 0.

0. , 0. , 0. , 0. , 0.13333333, 0. , 0.04603602, 0. , 0. , 0. , 0. , 0.
                   0.20628734, 0.2004597, 0.20045939, 0.19047619, 1.
                   0. , 0. , 0.05070514, 0. , 0.
                  0.25 , 0. , 0.05263158, 0. , 0. 
0. , 0. , 0. , 0.2 , 0. 
0. , 0.14285714, 0. , 0. , 0. 
0.09784827, 0. , 0.11990725, 0. , 0.
                   0.69662921, 0.0978495 , 0.10359226, 0.10359278, 0.
                   0. , 0. , 0. , 0. , 0.55555556,
                              , 0.03018689, 0.57142857, 0.08089288, 0.08072289,
                   0.22727273, 0. , 0. , 1. , 0.1262606 ])
In [38]: from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
           y_pred = regressor.predict(X_test)
           mse = mean_squared_error(y_test, y_pred)
           mae = mean_absolute_error(y_test, y_pred)
           r2 = r2_score(y_test, y_pred)
           32/32 [======== ] - 0s 3ms/step
```

Метрики работы MSE, MAE, R2

```
In [39]: print(f"MSE: {mse}")
    print(f"MAE: {mae}")
    print(f"R2: {r2}")

MSE: 1588.583464797732
    MAE: 28.06361318617011
    R2: 0.9999828651563029
In []:
```