Домашнее задание

по теме «RF Regressor, Feature engineering»

Библиотеки

In [1]:
```
# Импорт библиотек
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import zipfile

from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

from feature_engine.creation import MathFeatures
```

Подготовка данных

In [2]:
```
# Загрузка данных
archive_path = 'data/train.zip'
with zipfile.ZipFile(archive_path, 'r') as archive:

    with archive.open('train.csv') as file:
        df = pd.read_csv(file)
df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1200000 entries, 0 to 1199999
Data columns (total 21 columns):
 #   Column                Non-Null Count    Dtype  
---  ------                --------------    -----  
 0   id                    1200000 non-null  int64  
 1   Age                   1181295 non-null  float64
 2   Gender                1200000 non-null  object 
 3   Annual Income         1155051 non-null  float64
 4   Marital Status        1181471 non-null  object 
 5   Number of Dependents  1090328 non-null  float64
 6   Education Level       1200000 non-null  object 
 7   Occupation            841925 non-null   object 
 8   Health Score          1125924 non-null  float64
 9   Location              1200000 non-null  object 
 10  Policy Type           1200000 non-null  object 
 11  Previous Claims       835971 non-null   float64
 12  Vehicle Age           1199994 non-null  float64
 13  Credit Score          1062118 non-null  float64
 14  Insurance Duration    1199999 non-null  float64
 15  Policy Start Date     1200000 non-null  object 
 16  Customer Feedback     1122176 non-null  object 
 17  Smoking Status        1200000 non-null  object 
 18  Exercise Frequency    1200000 non-null  object 
 19  Property Type         1200000 non-null  object 
 20  Premium Amount        1200000 non-null  float64
dtypes: float64(9), int64(1), object(11)
memory usage: 192.3+ MB
```

Out[2]:

	id	Age	Gender	Annual Income	Marital Status	Number of Dependents	Education Level	Occupation	Health Score	Location	...	Previous Claims	Vehicle Age	Credit Score	Insuranc Duratio
0	0	19.0	Female	10049.0	Married	1.0	Bachelor's	Self-Employed	22.598761	Urban	...	2.0	17.0	372.0	5.
1	1	39.0	Female	31678.0	Divorced	3.0	Master's	NaN	15.569731	Rural	...	1.0	12.0	694.0	2.
2	2	23.0	Male	25602.0	Divorced	3.0	High School	Self-Employed	47.177549	Suburban	...	1.0	14.0	NaN	3.
3	3	21.0	Male	141855.0	Married	2.0	Bachelor's	NaN	10.938144	Rural	...	1.0	0.0	367.0	1.
4	4	21.0	Male	39651.0	Single	1.0	Bachelor's	Self-Employed	20.376094	Rural	...	0.0	8.0	598.0	4.

5 rows × 21 columns

In [3]:
```
# Переименование столбцов
df.columns = df.columns.str.replace(r'\(', '_', regex=True)
df.columns = df.columns.str.replace(r'\)', '', regex=True)
df.columns = df.columns.str.lower().str.replace(' ', '_')
```

In [4]:
```
df = df.drop(columns=['customer_feedback', 'policy_start_date'])
```

In [5]:
```
df = df.dropna()
```

In [6]:
```
df = df.sample(n=5000, random_state=42)
```

In [7]:
```
# Корректировка выбросов по верхней границе
def get_iqr_bounds(column):
    Q1 = column.quantile(0.25)
    Q3 = column.quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
```

```python
    return lower_bound, upper_bound

# Вычисление границы для каждого столбца
l_lower, l_upper = get_iqr_bounds(df['annual_income'])
df['annual_income'] = df['annual_income'].clip(upper=l_upper)

l_lower, l_upper = get_iqr_bounds(df['premium_amount'])
df['premium_amount'] = df['premium_amount'].clip(upper=l_upper)

l_lower, l_upper = get_iqr_bounds(df['previous_claims'])
df['previous_claims'] = df['previous_claims'].clip(upper=l_upper)
```

In [8]:

```python
# Кодирование категориальных фичей
df = pd.get_dummies(df, columns=[
    'gender',
    'marital_status',
    'education_level',
    'occupation',
    'location',
    'policy_type',
    'smoking_status',
    'exercise_frequency',
    'property_type'],drop_first=True)
```

In [9]:

```python
df.describe(include='all').T
```

Out[9]:

	count	unique	top	freq	mean	std	min	25%	50%	75%	ma
id	5000.0	NaN	NaN	NaN	597189.1392	344271.693762	762.0	303449.75	592803.0	889932.75	1199693.
age	5000.0	NaN	NaN	NaN	41.0992	13.566214	18.0	29.0	41.0	53.0	64.
annual_income	5000.0	NaN	NaN	NaN	31958.9355	29631.894824	17.0	7695.25	23777.0	45163.0	101364.62
number_of_dependents	5000.0	NaN	NaN	NaN	2.0318	1.415906	0.0	1.0	2.0	3.0	4.
health_score	5000.0	NaN	NaN	NaN	25.506605	12.146654	2.293558	15.950044	24.288681	34.471524	53.8468
previous_claims	5000.0	NaN	NaN	NaN	1.0316	0.997998	0.0	0.0	1.0	2.0	5.
vehicle_age	5000.0	NaN	NaN	NaN	9.4838	5.844499	0.0	4.0	9.0	15.0	19.
credit_score	5000.0	NaN	NaN	NaN	595.625	146.864819	300.0	476.0	598.0	718.0	849.
insurance_duration	5000.0	NaN	NaN	NaN	5.0546	2.589471	1.0	3.0	5.0	7.0	9.
premium_amount	5000.0	NaN	NaN	NaN	1104.2892	815.391715	20.0	522.0	889.0	1551.0	3094.
gender_Male	5000	2	True	2576	NaN	NaN	NaN	NaN	NaN	NaN	Nal
marital_status_Married	5000	2	False	3325	NaN	NaN	NaN	NaN	NaN	NaN	Nal
marital_status_Single	5000	2	False	3333	NaN	NaN	NaN	NaN	NaN	NaN	Nal
education_level_High School	5000	2	False	3798	NaN	NaN	NaN	NaN	NaN	NaN	Nal
education_level_Master's	5000	2	False	3733	NaN	NaN	NaN	NaN	NaN	NaN	Nal
education_level_PhD	5000	2	False	3746	NaN	NaN	NaN	NaN	NaN	NaN	Nal
occupation_Self-Employed	5000	2	False	3361	NaN	NaN	NaN	NaN	NaN	NaN	Nal
occupation_Unemployed	5000	2	False	3335	NaN	NaN	NaN	NaN	NaN	NaN	Nal
location_Suburban	5000	2	False	3319	NaN	NaN	NaN	NaN	NaN	NaN	Nal
location_Urban	5000	2	False	3321	NaN	NaN	NaN	NaN	NaN	NaN	Nal
policy_type_Comprehensive	5000	2	False	3325	NaN	NaN	NaN	NaN	NaN	NaN	Nal

	count	unique	top	freq	mean	std	min	25%	50%	75%	ma
policy_type_Premium	5000	2	False	3354	NaN	NaN	NaN	NaN	NaN	NaN	Nal
smoking_status_Yes	5000	2	False	2510	NaN	NaN	NaN	NaN	NaN	NaN	Nal
exercise_frequency_Monthly	5000	2	False	3719	NaN	NaN	NaN	NaN	NaN	NaN	Nal
exercise_frequency_Rarely	5000	2	False	3767	NaN	NaN	NaN	NaN	NaN	NaN	Nal
exercise_frequency_Weekly	5000	2	False	3710	NaN	NaN	NaN	NaN	NaN	NaN	Nal
property_type_Condo	5000	2	False	3323	NaN	NaN	NaN	NaN	NaN	NaN	Nal
property_type_House	5000	2	False	3326	NaN	NaN	NaN	NaN	NaN	NaN	Nal

In [10]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 5000 entries, 678562 to 208907
Data columns (total 28 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   id                            5000 non-null   int64  
 1   age                           5000 non-null   float64
 2   annual_income                 5000 non-null   float64
 3   number_of_dependents          5000 non-null   float64
 4   health_score                  5000 non-null   float64
 5   previous_claims               5000 non-null   float64
 6   vehicle_age                   5000 non-null   float64
 7   credit_score                  5000 non-null   float64
 8   insurance_duration            5000 non-null   float64
 9   premium_amount                5000 non-null   float64
 10  gender_Male                   5000 non-null   bool   
 11  marital_status_Married        5000 non-null   bool   
 12  marital_status_Single         5000 non-null   bool   
 13  education_level_High School   5000 non-null   bool   
 14  education_level_Master's      5000 non-null   bool   
 15  education_level_PhD           5000 non-null   bool   
 16  occupation_Self-Employed      5000 non-null   bool   
 17  occupation_Unemployed         5000 non-null   bool   
 18  location_Suburban             5000 non-null   bool   
 19  location_Urban                5000 non-null   bool   
 20  policy_type_Comprehensive     5000 non-null   bool   
 21  policy_type_Premium           5000 non-null   bool   
 22  smoking_status_Yes            5000 non-null   bool   
 23  exercise_frequency_Monthly    5000 non-null   bool   
 24  exercise_frequency_Rarely     5000 non-null   bool   
 25  exercise_frequency_Weekly     5000 non-null   bool   
 26  property_type_Condo           5000 non-null   bool   
 27  property_type_House           5000 non-null   bool   
dtypes: bool(18), float64(9), int64(1)
memory usage: 517.6 KB
```

Выборки

In [11]:
```
# Подготовка данных
X = df.drop(['premium_amount','id'], axis=1)
```

```python
y = df['premium_amount']

# Разделение на обучающую и тестовую выборки
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.2,
    random_state=42
)
```

Подбор гиперпараметров

In [12]:

```python
# Определяем сетку гиперпараметров
param_grid = {
    'n_estimators': [300, 500, 1000],  # Количество деревьев
    'max_depth': [None, 10, 20, 30],   # Максимальная глубина дерева
    'min_samples_split': [2, 5],   # Минимальное количество образцов для разделения
    'min_samples_leaf': [4, 6],     # Минимальное количество образцов в листе
    'max_features': ['sqrt', 'log2']   # Количество признаков для поиска лучшего разделения
}

# Создаем модель
model = RandomForestRegressor(random_state=42)

# Инициализируем GridSearchCV
grid_search = GridSearchCV(
    estimator=model,
    param_grid=param_grid,
    scoring='neg_mean_squared_error',
    cv=5,
    n_jobs=-1,
    verbose=2
)

# Запускаем поиск по сетке
grid_search.fit(X_train, y_train)

# Лучшие параметры
print("Лучшие параметры:", grid_search.best_params_)
```

```
# Лучшая модель
best_model = grid_search.best_estimator_
```

```
Fitting 5 folds for each of 96 candidates, totalling 480 fits
Лучшие параметры: {'max_depth': 10, 'max_features': 'sqrt', 'min_samples_leaf': 6, 'min_samples_split': 2, 'n_estimators': 300}
```

RandomForestRegressor на исходных данных

In [13]:
```
# fit
best_model.fit(X_train, y_train)
```

Out[13]:
```
RandomForestRegressor

RandomForestRegressor(max_depth=10, max_features='sqrt', min_samples_leaf=6,
                      n_estimators=300, random_state=42)
```

In [14]:
```
# Предсказание на тестовой выборке
y_pred = best_model.predict(X_test)

# Оценка качества модели
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f'MSE: {mse:.2f}')
print(f'MAE: {mae:.2f}')
print(f'R²: {r2:.4f}')
```

```
MSE: 628204.30
MAE: 639.67
R²: 0.0177
```

Выводы:

- MSE (Mean Squared Error) = 628204.30 Очень высокое значение MSE указывает на то, что модель делает большие ошибки в предсказаниях.
- MAE (Mean Absolute Error) = 639.67 Высокое значение MAE подтверждает, что модель ошибается в предсказаниях.
- R^2 (Коэффициент детерминации) = 0.0177 Значение R^2 близко к 0, модель не объясняет целевую переменную.

- Модель не работает!

Применение библиотеки feature-engine к набору данных

In [ ]:
```
# для генерации новых признаков путем математических операций
MF = MathFeatures(
    # Список признаков для комбинации
    # Беру связку самого важной фичи и таргет
    # ===== ожидаю переобучение =====
    variables=["annual_income", "premium_amount"],
    func=["sum", "min", "max", "std"]
)

# fit
MF.fit(df)

# Применение трансформации к данным
df_math = MF.transform(df)
```

Изучение новых столбцо и удаление NaN и нулевых значений

In [16]:
```
df_math.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 5000 entries, 678562 to 208907
Data columns (total 32 columns):
 #   Column                           Non-Null Count  Dtype  
---  ------                           --------------  -----  
 0   id                               5000 non-null   int64  
 1   age                              5000 non-null   float64
 2   annual_income                    5000 non-null   float64
 3   number_of_dependents             5000 non-null   float64
 4   health_score                     5000 non-null   float64
 5   previous_claims                  5000 non-null   float64
 6   vehicle_age                      5000 non-null   float64
 7   credit_score                     5000 non-null   float64
 8   insurance_duration               5000 non-null   float64
 9   premium_amount                   5000 non-null   float64
 10  gender_Male                      5000 non-null   bool   
 11  marital_status_Married           5000 non-null   bool   
 12  marital_status_Single            5000 non-null   bool   
 13  education_level_High School      5000 non-null   bool   
 14  education_level_Master's         5000 non-null   bool   
 15  education_level_PhD              5000 non-null   bool   
 16  occupation_Self-Employed         5000 non-null   bool   
 17  occupation_Unemployed            5000 non-null   bool   
 18  location_Suburban                5000 non-null   bool   
 19  location_Urban                   5000 non-null   bool   
 20  policy_type_Comprehensive        5000 non-null   bool   
 21  policy_type_Premium              5000 non-null   bool   
 22  smoking_status_Yes               5000 non-null   bool   
 23  exercise_frequency_Monthly       5000 non-null   bool   
 24  exercise_frequency_Rarely        5000 non-null   bool   
 25  exercise_frequency_Weekly        5000 non-null   bool   
 26  property_type_Condo              5000 non-null   bool   
 27  property_type_House              5000 non-null   bool   
 28  sum_annual_income_premium_amount  5000 non-null   float64
 29  min_annual_income_premium_amount  5000 non-null   float64
 30  max_annual_income_premium_amount  5000 non-null   float64
 31  std_annual_income_premium_amount  5000 non-null   float64
dtypes: bool(18), float64(13), int64(1)
memory usage: 673.8 KB
```

Генерированно 4 новых столбца

In [17]:
```python
df_new = df_math[[
    'sum_annual_income_premium_amount',
    'min_annual_income_premium_amount',
    'max_annual_income_premium_amount',
    'std_annual_income_premium_amount'
]]
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 5000 entries, 678562 to 208907
Data columns (total 4 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   sum_annual_income_premium_amount  5000 non-null   float64
 1   min_annual_income_premium_amount  5000 non-null   float64
 2   max_annual_income_premium_amount  5000 non-null   float64
 3   std_annual_income_premium_amount  5000 non-null   float64
dtypes: float64(4)
memory usage: 195.3 KB
```

In [18]:
```python
df_new.describe(include='all')
```

Out[18]:

	sum_annual_income_premium_amount	min_annual_income_premium_amount	max_annual_income_premium_amount	std_annual_incom
count	5000.000000	5000.000000	5000.000000	
mean	33063.224700	1068.862000	31994.362700	
std	29666.947024	793.962764	29595.515575	
min	70.000000	17.000000	45.000000	
25%	8585.500000	511.000000	7695.250000	
50%	24707.500000	854.000000	23777.000000	
75%	46224.250000	1489.000000	45163.000000	
max	104459.125000	3094.500000	101364.625000	

In [19]:
```
nan_columns = df_new.columns[df_new.isna().any()].tolist()
print("Столбцы с NaN:", nan_columns)
```

```
Столбцы с NaN: []
```

In [20]:
```
zero_percentage = (df_new == 0).mean() * 100
print("Доля нулей (%):")
print(zero_percentage)
```

```
Доля нулей (%):
sum_annual_income_premium_amount    0.00
min_annual_income_premium_amount    0.00
max_annual_income_premium_amount    0.00
std_annual_income_premium_amount    0.06
dtype: float64
```

В новых столбцах нулей и пропусков нет

Обучение на генерированных данных

In [21]:
```
# Подготовка данных
X = df_math.drop(['premium_amount','id'], axis=1)
y = df_math['premium_amount']

# Разделение на обучающую и тестовую выборки
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.2,
    random_state=42
)

# Обучаю на тех же гиперпараметрах
best_model_math = grid_search.best_estimator_

# fit
best_model_math.fit(X_train, y_train)

# Предсказание на тестовой выборке
y_pred = best_model_math.predict(X_test)
```

```python
# Оценка качества модели
mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f'MSE: {mse:.2f}')
print(f'MAE: {mae:.2f}')
print(f'R²: {r2:.4f}')
```

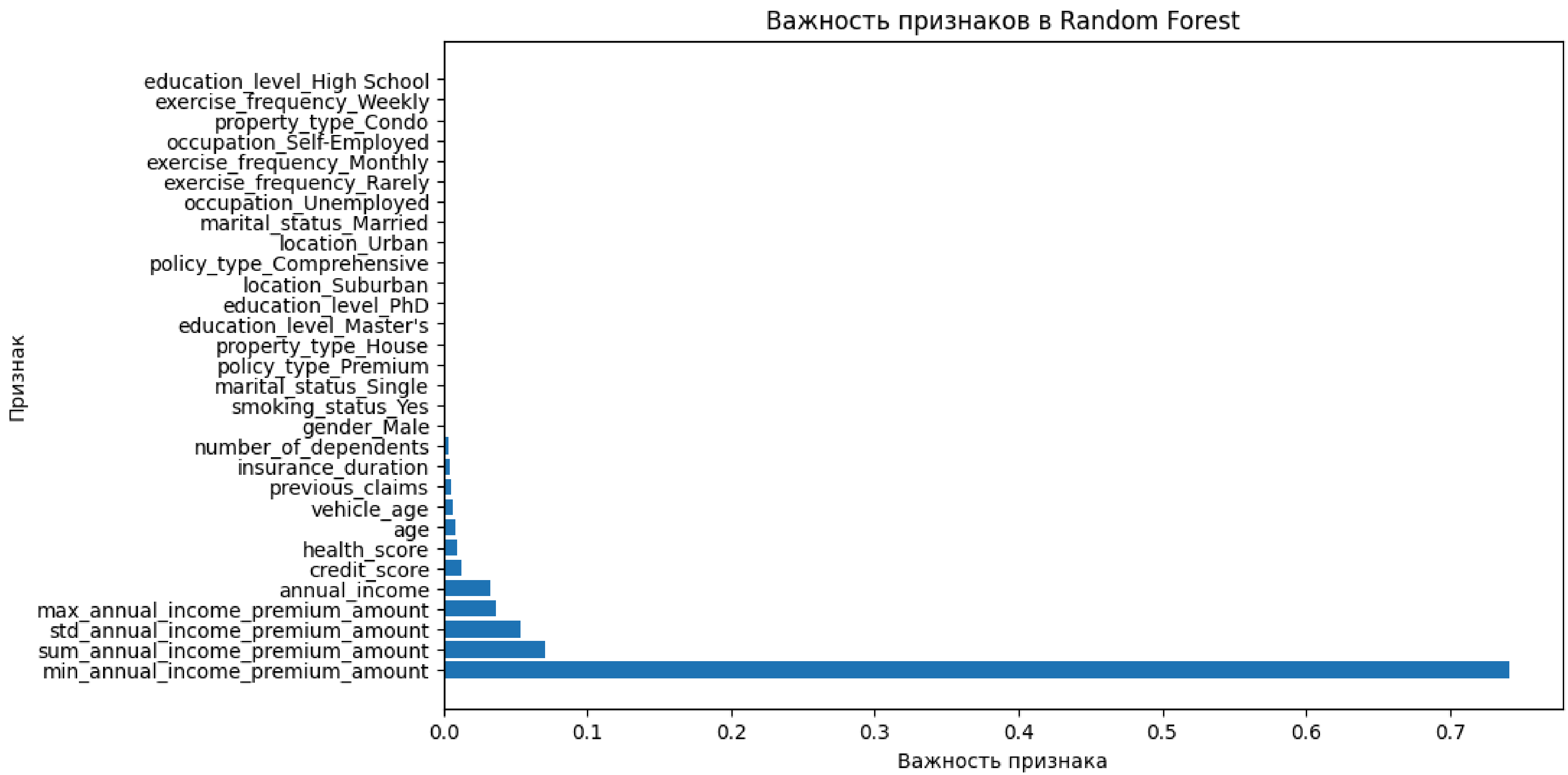
```
MSE: 75083.31
MAE: 190.99
R²: 0.8826
```

Выводы по новой модели

- Значительно снизилось MSE с 628204.30 до 75083.31
- MAE снизилось с 639.67 до 190.99
- R^2 выросло с 0.0177 до 0.8826
- модель показывает значительное улучшение метрик

In [22]:

```python
# Важность признаков
feature_importance = pd.DataFrame({
    "Feature": X.columns,
    "Importance": best_model.feature_importances_
}).sort_values("Importance", ascending=False)

# Визуализация
plt.figure(figsize=(10, 6))
plt.barh(feature_importance["Feature"], feature_importance["Importance"])
plt.xlabel("Важность признака")
plt.ylabel("Признак")
plt.title("Важность признаков в Random Forest")
plt.show()
```



In [23]:

```
# Получаем важность признаков
feature_importance = pd.DataFrame({
    "Feature": X.columns,
    "Importance": best_model.feature_importances_
}).sort_values("Importance", ascending=False)

# Топ-10 признаков
top_10 = feature_importance.head(10)
top_10
```

Out[23]:

	Feature	Importance
27	min_annual_income_premium_amount	0.741583
26	sum_annual_income_premium_amount	0.070313
29	std_annual_income_premium_amount	0.053765
28	max_annual_income_premium_amount	0.035990
1	annual_income	0.032295
6	credit_score	0.012201
3	health_score	0.009109
0	age	0.007741
5	vehicle_age	0.005690
4	previous_claims	0.005375

- Все 4 новых фичи вошли в ТОП-10
- 'min_annual_income_premium_amount' значительно опережает остальные параметры по важности.

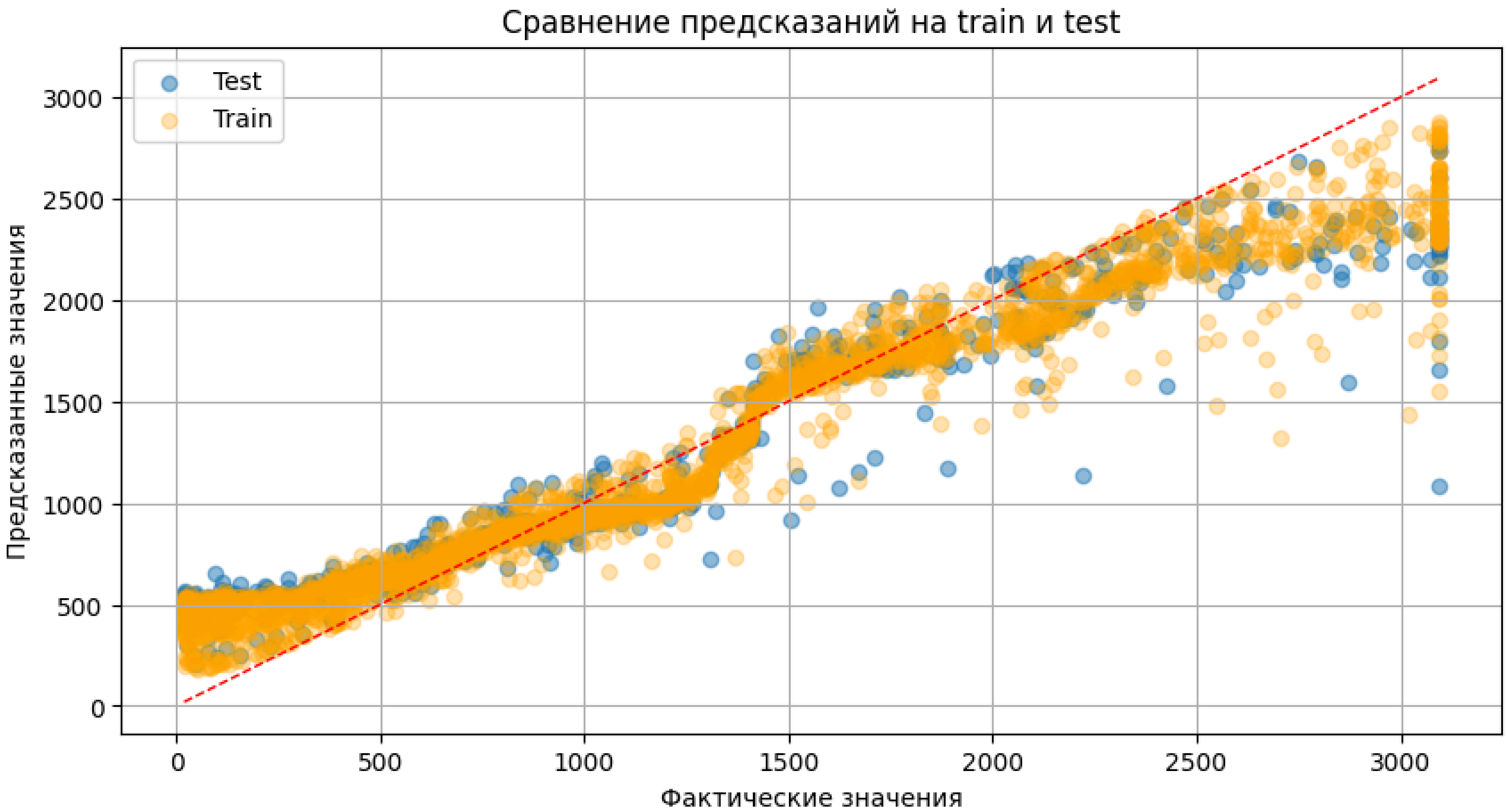
Проверка на переобучение

In [24]:

```
# В домашнем задании нет такой задачи делаю ради интереса
train_pred = best_model_math.predict(X_train)
test_pred = best_model_math.predict(X_test)

train_r2 = r2_score(y_train, train_pred)
test_r2 = r2_score(y_test, test_pred)

train_mse = mean_squared_error(y_train, train_pred)
test_mse = mean_squared_error(y_test, test_pred)

print("\nПроверка на переобучение:")
print(f"Train R²: {train_r2:.4f} | Test R²: {test_r2:.4f}")
```

```python
print(f"Train MSE: {train_mse:.2f} | Test MSE: {test_mse:.2f}")

r2_diff = abs(train_r2 - test_r2)
mse_diff = abs(train_mse - test_mse)/train_mse

print(f"\nРазница между train и test:")
print(f"R² difference: {r2_diff:.4f}")
print(f"MSE relative difference: {mse_diff:.1%}")

if r2_diff > 0.15 or mse_diff > 0.2:
    print("\nПризнаки переобучения:")
    if r2_diff > 0.15:
        print(f"- Большая разница в R² ({r2_diff:.2f} > 0.15)")
    if mse_diff > 0.2:
        print(f"- Большая разница в MSE ({mse_diff:.0%} > 20%)")
else:
    print("\nПризнаков переобучения не обнаружено")

# График
plt.figure(figsize=(10, 5))
plt.scatter(y_test, test_pred, alpha=0.5, label='Test')
plt.scatter(y_train, train_pred, alpha=0.3, label='Train', color='orange')
plt.plot([min(y), max(y)], [min(y), max(y)], '--r', linewidth=1)
plt.xlabel('Фактические значения')
plt.ylabel('Предсказанные значения')
plt.title('Сравнение предсказаний на train и test')
plt.legend()
plt.grid(True)
plt.show()
```

```
Проверка на переобучение:
Train R²: 0.9092 | Test R²: 0.8826
Train MSE: 60929.66 | Test MSE: 75083.31

Разница между train и test:
R² difference: 0.0266
MSE relative difference: 23.2%

Признаки переобучения:
- Большая разница в MSE (23% > 20%)
```



Новая модель с генерированными параметрами имеет признаки переобучения.

Вводы по домашней работе

- Feature engineering помогает улучшить качество моделей
- Инструменты автоматизации позволяют ускорить процесс создания новых параметров
- В любом случае требуется детальный анализ генерированных параметров и изучение предметной области