In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
sns.set_theme(color_codes=True)
```

In [2]:
```
df = pd.read_csv('train_BRCpofr.csv')
df.head()
```

Out[2]:

	id	gender	area	qualification	income	marital_status	vintage	claim_amount	num_policies	policy	type_of_policy
0	1	Male	Urban	Bachelor	5L-10L	1	5	5790	More than 1	A	Platinum
1	2	Male	Rural	High School	5L-10L	0	8	5080	More than 1	A	Platinum
2	3	Male	Urban	Bachelor	5L-10L	1	8	2599	More than 1	A	Platinum
3	4	Female	Rural	High School	5L-10L	0	7	0	More than 1	A	Platinum
4	5	Male	Urban	High School	More than 10L	1	6	3508	More than 1	A	Gold

Data Preprocessing Part 1

In [3]:
```
#Check the number of unique value from all of the object datatype
df.select_dtypes(include='object').nunique()
```

Out[3]:
```
gender            2
area              2
qualification     3
income            4
num_policies      2
policy            3
type_of_policy    3
dtype: int64
```

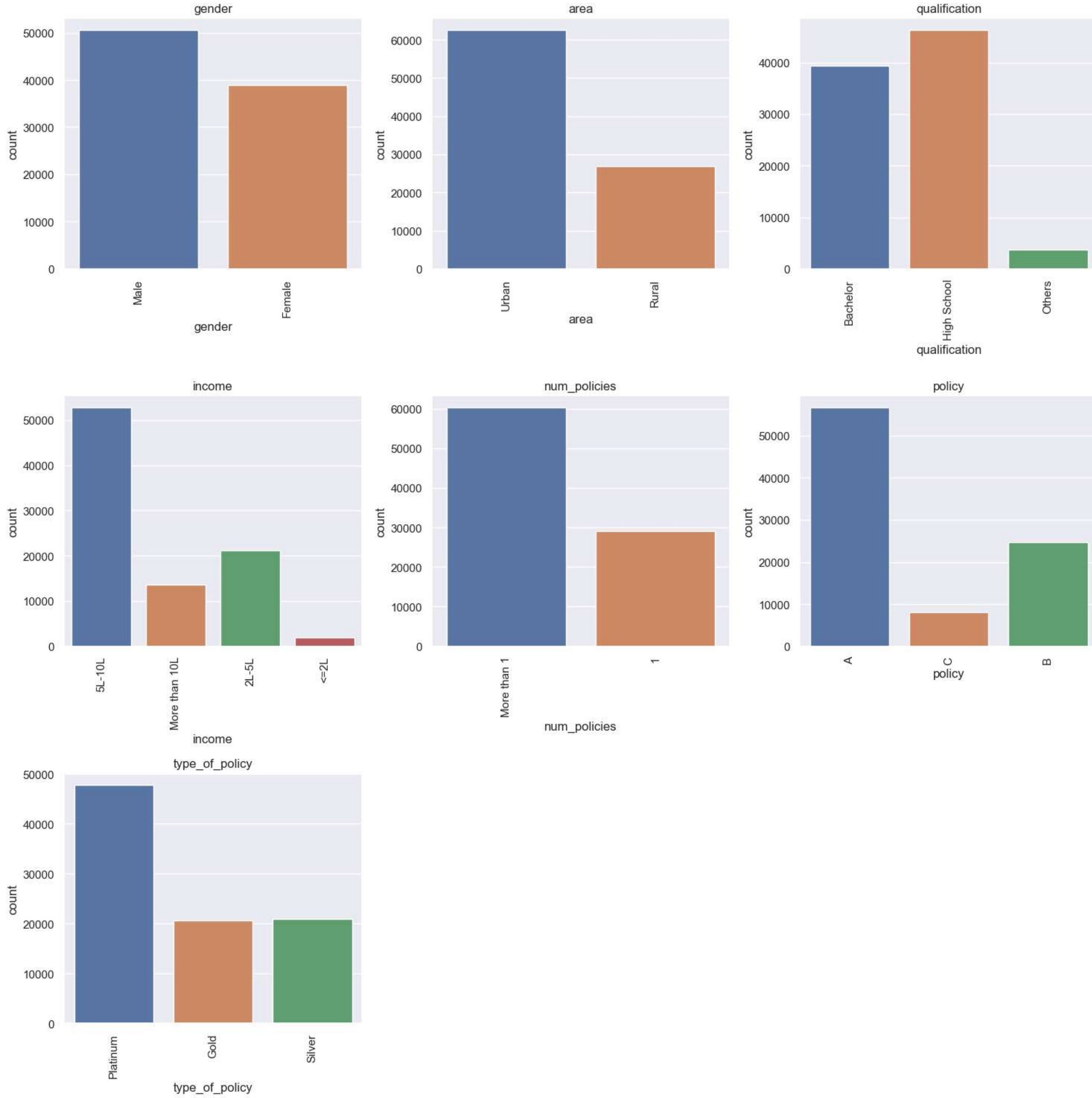
In [4]:
```
# Remove identifier columns
df.drop(columns = 'id', inplace=True)
df.head()
```

Out[4]:

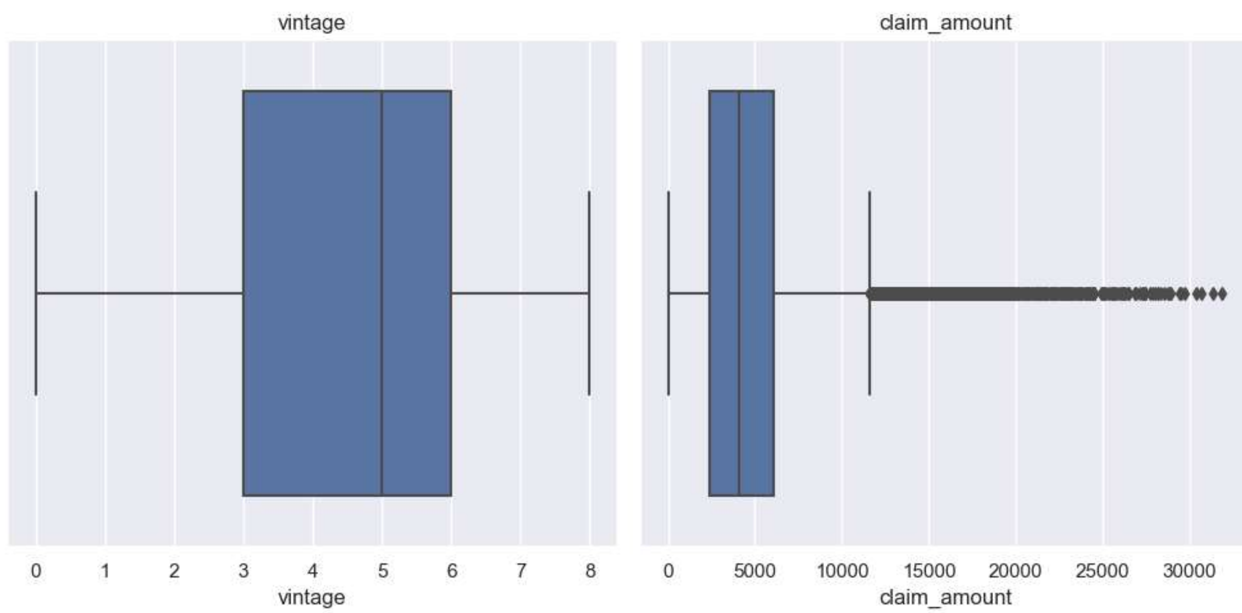
	gender	area	qualification	income	marital_status	vintage	claim_amount	num_policies	policy	type_of_policy	
0	Male	Urban	Bachelor	5L-10L	1	5	5790	More than 1	A	Platinum	64
1	Male	Rural	High School	5L-10L	0	8	5080	More than 1	A	Platinum	515
2	Male	Urban	Bachelor	5L-10L	1	8	2599	More than 1	A	Platinum	64
3	Female	Rural	High School	5L-10L	0	7	0	More than 1	A	Platinum	97
4	Male	Urban	High School	More than 10L	1	6	3508	More than 1	A	Gold	59

Exploratory Data Analysis

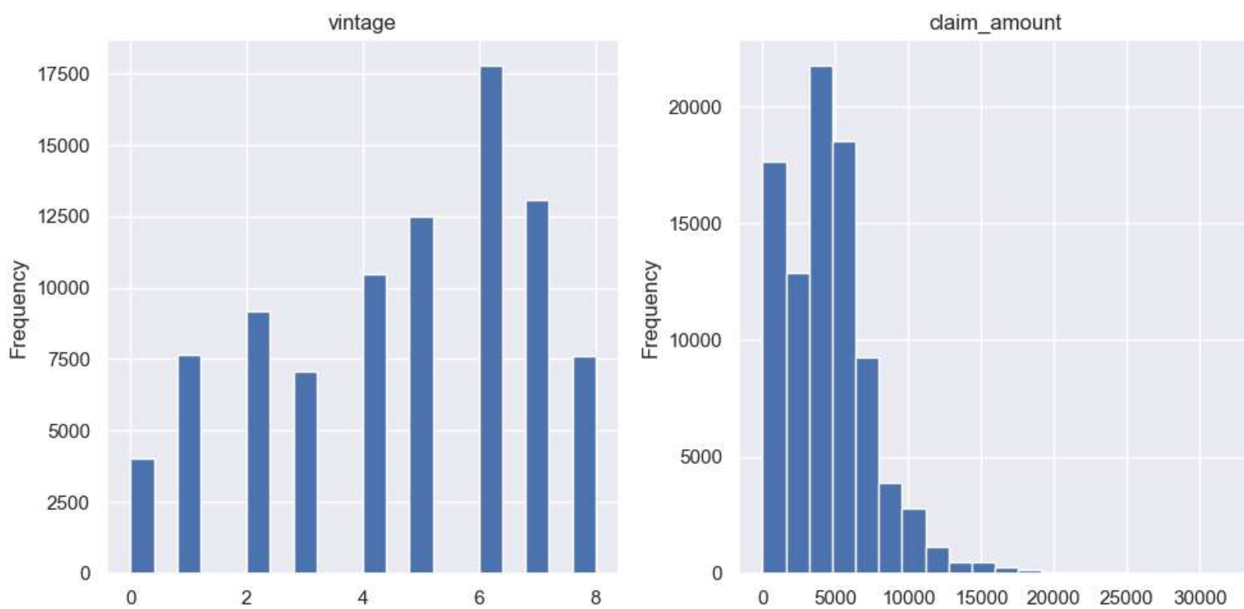
In [5]:
```
# Get the names of all columns with data type 'object' (categorical columns)
cat_vars = df.select_dtypes(include='object').columns.tolist()

# Create a figure with subplots
num_cols = len(cat_vars)
num_rows = (num_cols + 2) // 3
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Create a countplot for the top 6 values of each categorical variable using Seaborn
for i, var in enumerate(cat_vars):
    top_values = df[var].value_counts().nlargest(6).index
    filtered_df = df[df[var].isin(top_values)]
    sns.countplot(x=var, data=filtered_df, ax=axs[i])
    axs[i].set_title(var)
    axs[i].tick_params(axis='x', rotation=90)

# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust spacing between subplots
fig.tight_layout()

# Show plot
plt.show()
```


gender
count
Male
Female
gender
area
Urban
Rural
area
qualification
Bachelor
High School
Others
qualification
income
5L-10L
More than 10L
2L-5L
<=2L
income
num_policies
More than 1
1
num_policies
policy
A
C
B
policy
type_of_policy
Platinum
Gold
Silver
type_of_policy

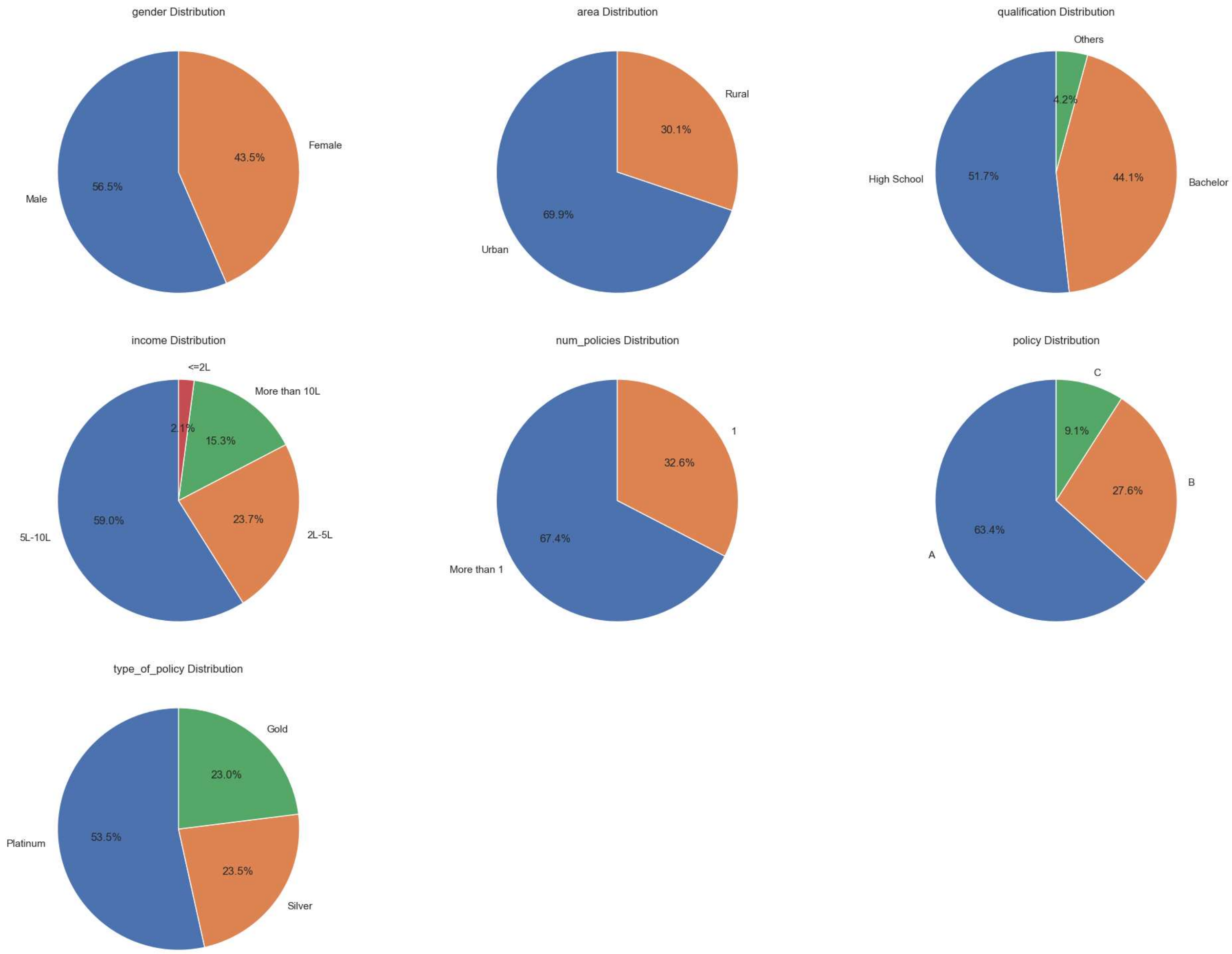
In [7]:
```
# Get the names of all columns with data type 'int' or 'float' except 'cltv' and 'marital_status'
num_vars = df.select_dtypes(include=['int', 'float']).columns.tolist()
exclude_vars = ['cltv', 'marital_status']
num_vars = [var for var in num_vars if var not in exclude_vars]

# Create a figure with subplots
num_cols = len(num_vars)
num_rows = (num_cols + 2) // 3
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Create a box plot for each numerical variable using Seaborn
for i, var in enumerate(num_vars):
    sns.boxplot(x=df[var], ax=axs[i])
    axs[i].set_title(var)

# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust spacing between subplots
fig.tight_layout()

# Show plot
plt.show()
```



In [8]:
```
# Get the names of all columns with data type 'int' or 'float' except 'marital_status' and 'cltv'
int_vars = df.select_dtypes(include=['int', 'float']).columns.tolist()
exclude_vars = ['marital_status', 'cltv']
int_vars = [var for var in int_vars if var not in exclude_vars]

# Create a figure with subplots
num_cols = len(int_vars)
num_rows = (num_cols + 2) // 3  # To make sure there are enough rows for the subplots
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(15, 5*num_rows))
axs = axs.flatten()

# Create a histogram for each integer variable
for i, var in enumerate(int_vars):
    df[var].plot.hist(ax=axs[i], bins=20)  # You can adjust the number of bins as needed
    axs[i].set_title(var)

# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust spacing between subplots
fig.tight_layout()

# Show plot
plt.show()
```



In [9]:
```
# Specify the maximum number of categories to show individually
max_categories = 5

# Filter categorical columns with 'object' data type
cat_cols = [col for col in df.columns if col != 'y' and df[col].dtype == 'object']

# Create a figure with subplots
num_cols = len(cat_cols)
num_rows = (num_cols + 2) // 3
fig, axs = plt.subplots(nrows=num_rows, ncols=3, figsize=(20, 5*num_rows))

# Flatten the axs array for easier indexing
axs = axs.flatten()

# Create a pie chart for each categorical column
for i, col in enumerate(cat_cols):
    if i < len(axs):  # Ensure we don't exceed the number of subplots
        # Count the number of occurrences for each category
        cat_counts = df[col].value_counts()

        # Group categories beyond the top max_categories as 'Other'
        if len(cat_counts) > max_categories:
            cat_counts_top = cat_counts[:max_categories]
            cat_counts_other = pd.Series(cat_counts[max_categories:].sum(), index=['Other'])
            cat_counts = cat_counts_top.append(cat_counts_other)

        # Create a pie chart
        axs[i].pie(cat_counts, labels=cat_counts.index, autopct='%1.1f%%', startangle=90)
        axs[i].set_title(f'{col} Distribution')

# Remove any extra empty subplots if needed
if num_cols < len(axs):
    for i in range(num_cols, len(axs)):
        fig.delaxes(axs[i])

# Adjust spacing between subplots
fig.tight_layout()

# Show plot
plt.show()
```



Data Preprocessing Part 2

In [10]:
```
# Check the amounnt of missing value
check_missing = df.isnull().sum() * 100 / df.shape[0]
check_missing[check_missing > 0].sort_values(ascending=False)
```

Out[10]:
```
Series([], dtype: float64)
```

Label Encoding for Object Datatypes

In [11]:
```
# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Print the column name and the unique values
    print(f"{col}: {df[col].unique()}")
```

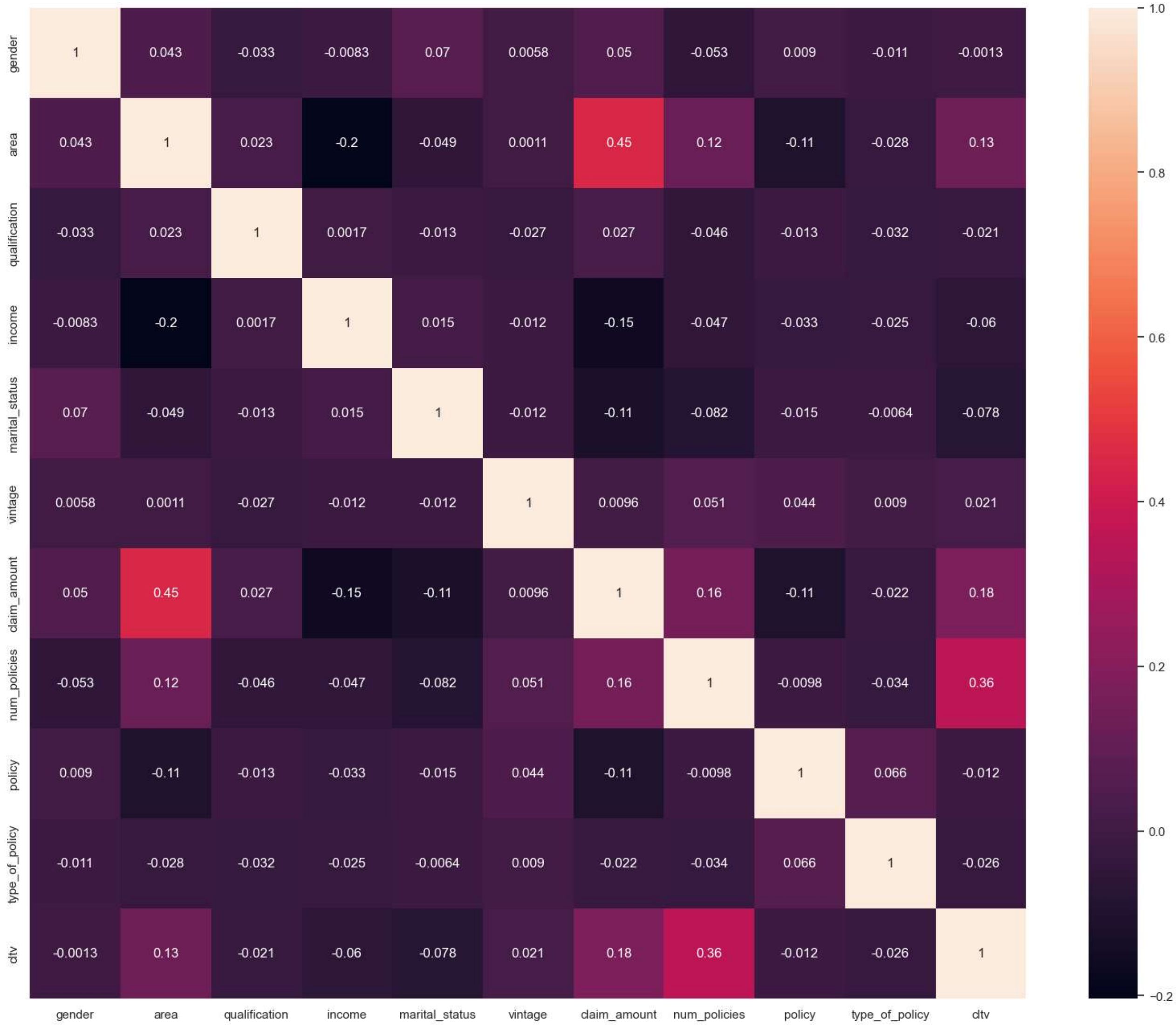
```
gender: ['Male' 'Female']
area: ['Urban' 'Rural']
qualification: ['Bachelor' 'High School' 'Others']
income: ['5L-10L' 'More than 10L' '2L-5L' '<=2L']
num_policies: ['More than 1' '1']
policy: ['A' 'C' 'B']
type_of_policy: ['Platinum' 'Gold' 'Silver']
```

In [12]:
```
from sklearn import preprocessing

# Loop over each column in the DataFrame where dtype is 'object'
for col in df.select_dtypes(include=['object']).columns:

    # Initialize a LabelEncoder object
    label_encoder = preprocessing.LabelEncoder()

    # Fit the encoder to the unique values in the column
    label_encoder.fit(df[col].unique())

    # Transform the column using the encoder
    df[col] = label_encoder.transform(df[col])

    # Print the column name and the unique encoded values
    print(f"{col}: {df[col].unique()}")
```

```
gender: [1 0]
area: [1 0]
qualification: [0 1 2]
income: [1 3 0 2]
num_policies: [1 0]
policy: [0 2 1]
type_of_policy: [1 0 2]
```

In [14]:
```
# Correlation Heatmap
plt.figure(figsize=(20, 16))
sns.heatmap(df.corr(), fmt='.2g', annot=True)
```

Out[14]: <AxesSubplot:>



Train Test Split

In [15]:
```
X = df.drop('cltv', axis=1)
y = df['cltv']
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.2,random_state=0)
```

Remove Outlier from Train Data using Z-Score

In [16]:
```
from scipy import stats

# Define the columns for which you want to remove outliers
selected_columns = ['claim_amount']

# Calculate the Z-scores for the selected columns in the training data
z_scores = np.abs(stats.zscore(X_train[selected_columns]))

# Set a threshold value for outlier detection (e.g., 3)
threshold = 3

# Find the indices of outliers based on the threshold
outlier_indices = np.where(z_scores > threshold)[0]

# Remove the outliers from the training data
X_train = X_train.drop(X_train.index[outlier_indices])
y_train = y_train.drop(y_train.index[outlier_indices])
```

Decision Tree Regressor

In [17]:
```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import GridSearchCV
from sklearn.datasets import load_boston


# Create a DecisionTreeRegressor object
dtree = DecisionTreeRegressor()

# Define the hyperparameters to tune and their values
param_grid = {
    'max_depth': [2, 4, 6, 8],
    'min_samples_split': [2, 4, 6, 8],
    'min_samples_leaf': [1, 2, 3, 4],
    'max_features': ['auto', 'sqrt', 'log2'],
    'random_state': [0, 42]
}

# Create a GridSearchCV object
grid_search = GridSearchCV(dtree, param_grid, cv=5, scoring='neg_mean_squared_error')

# Fit the GridSearchCV object to the data
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print(grid_search.best_params_)
```

```
{'max_depth': 4, 'max_features': 'auto', 'min_samples_leaf': 1, 'min_samples_split': 2, 'random_
state': 0}
```

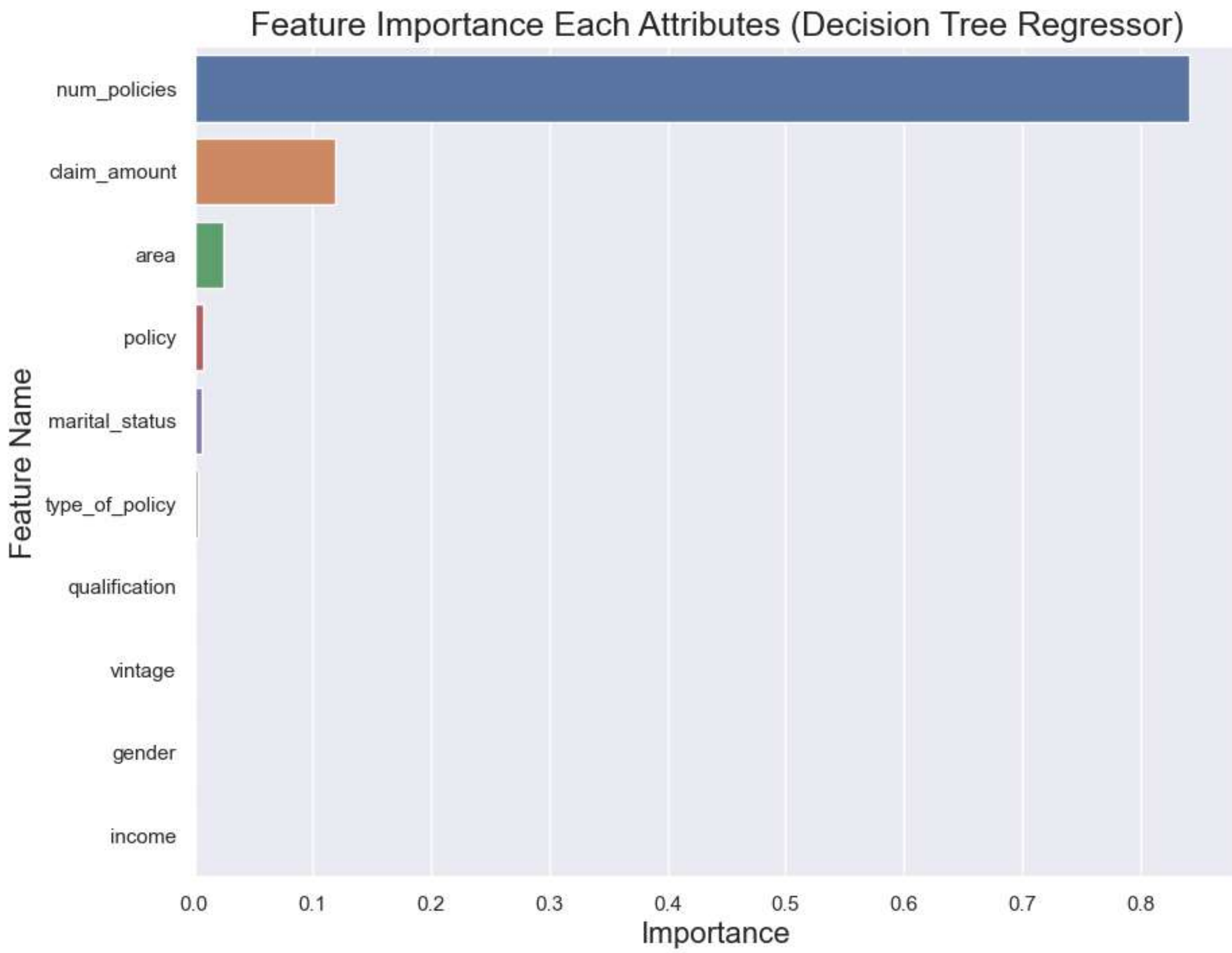
In [18]:
```
from sklearn.tree import DecisionTreeRegressor
dtree = DecisionTreeRegressor(random_state=0, max_depth=4, max_features='auto', min_samples_leaf=
dtree.fit(X_train, y_train)
```

Out[18]:
```
DecisionTreeRegressor(max_depth=4, max_features='auto', random_state=0)
```

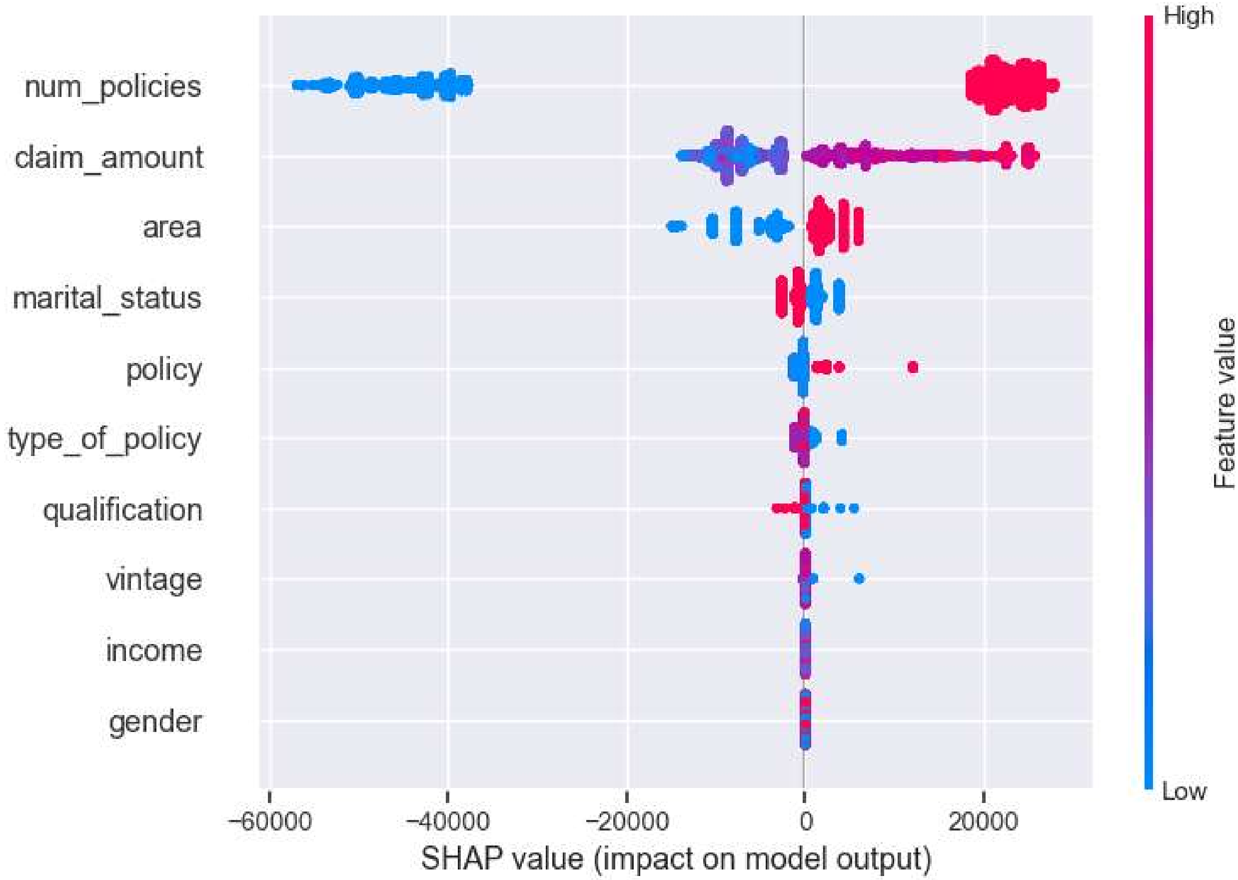
In [19]:
```
from sklearn import metrics
from sklearn.metrics import mean_absolute_percentage_error
import math
y_pred = dtree.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

print('MAE is {}'.format(mae))
print('MAPE is {}'.format(mape))
print('MSE is {}'.format(mse))
print('R2 score is {}'.format(r2))
print('RMSE score is {}'.format(rmse))
```

```
MAE is 50628.65370829872
MAPE is 0.5470793080704087
MSE is 6871635638.508964
R2 score is 0.15912384513589772
RMSE score is 82895.32941311569
```

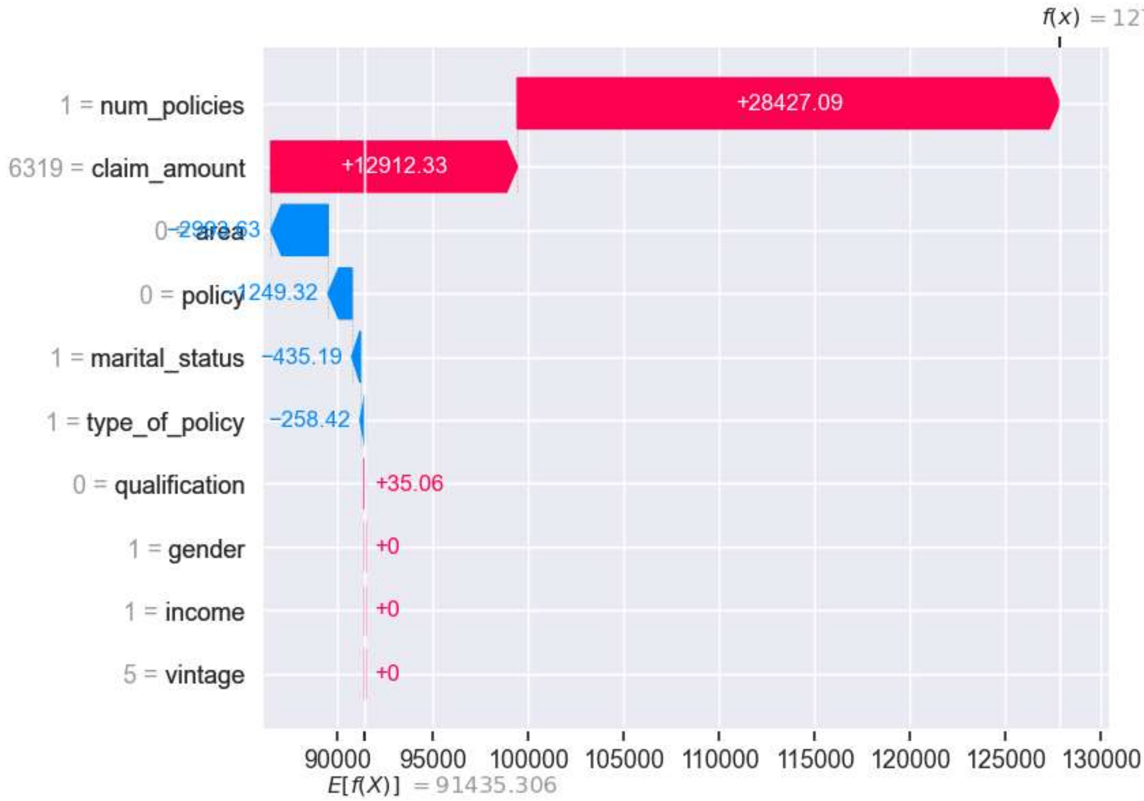
In [20]:
```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": dtree.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Feature Importance Each Attributes (Decision Tree Regressor)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



In [21]:
```
import shap
explainer = shap.TreeExplainer(dtree)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```



In [22]:
```
explainer = shap.Explainer(dtree, X_test)
shap_values = explainer(X_test)
shap.plots.waterfall(shap_values[0])
```



Random Forest Regressor

In [23]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV

# Create a Random Forest Regressor object
rf = RandomForestRegressor()

# Define the hyperparameter grid
param_grid = {
    'max_depth': [3, 5, 7, 9],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt'],
    'random_state': [0, 42]
}

# Create a GridSearchCV object
grid_search = GridSearchCV(rf, param_grid, cv=5, scoring='r2')

# Fit the GridSearchCV object to the training data
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print("Best hyperparameters: ", grid_search.best_params_)
```

```
Best hyperparameters:  {'max_depth': 9, 'max_features': 'sqrt', 'min_samples_leaf': 1, 'min_samp
les_split': 10, 'random_state': 0}
```

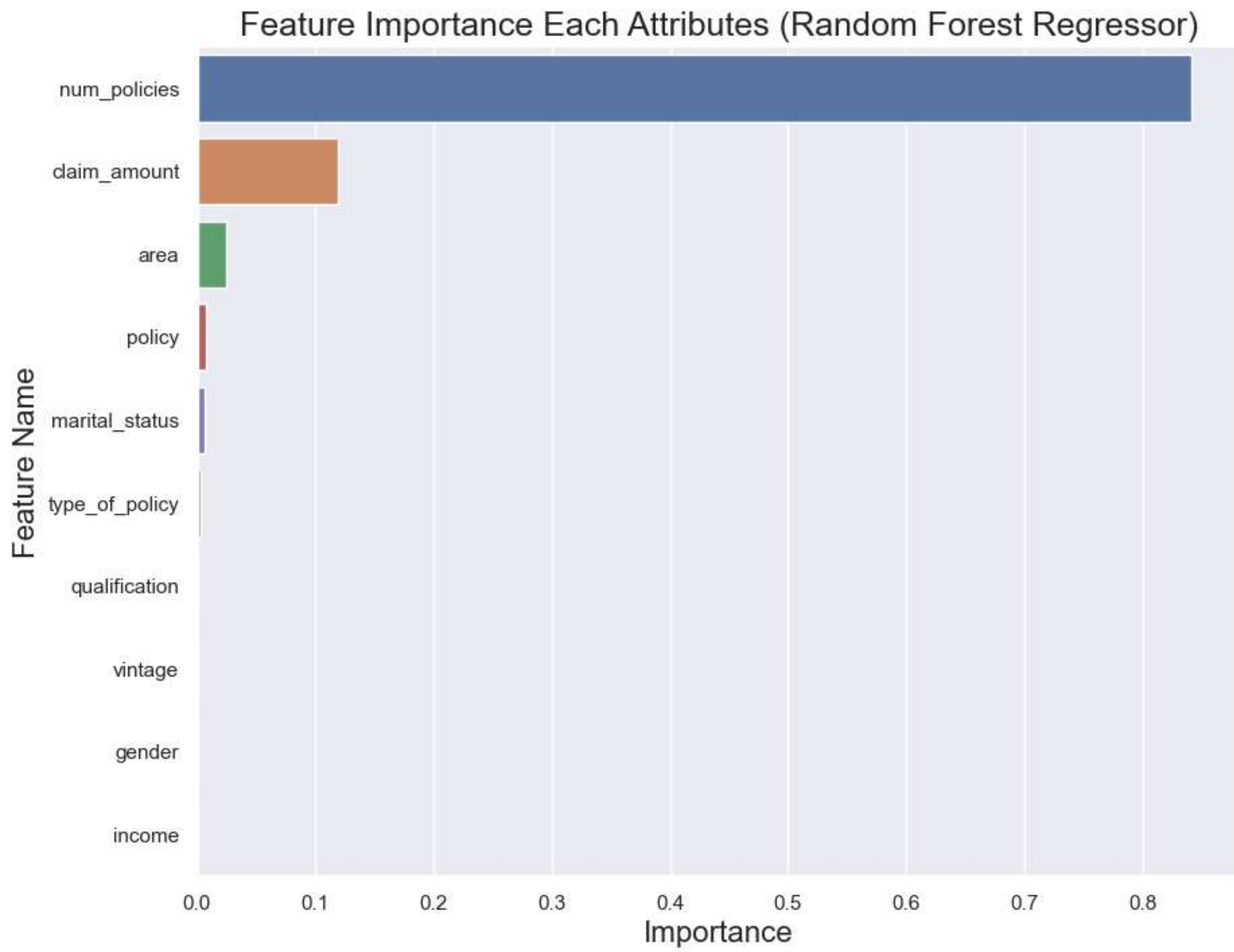
In [24]:
```
from sklearn.ensemble import RandomForestRegressor
rf = RandomForestRegressor(random_state=0, max_depth=9, min_samples_split=10, min_samples_leaf=1,
                           max_features='sqrt')
rf.fit(X_train, y_train)
```

Out[24]:
```
RandomForestRegressor(max_depth=9, max_features='sqrt', min_samples_split=10,
                      random_state=0)
```

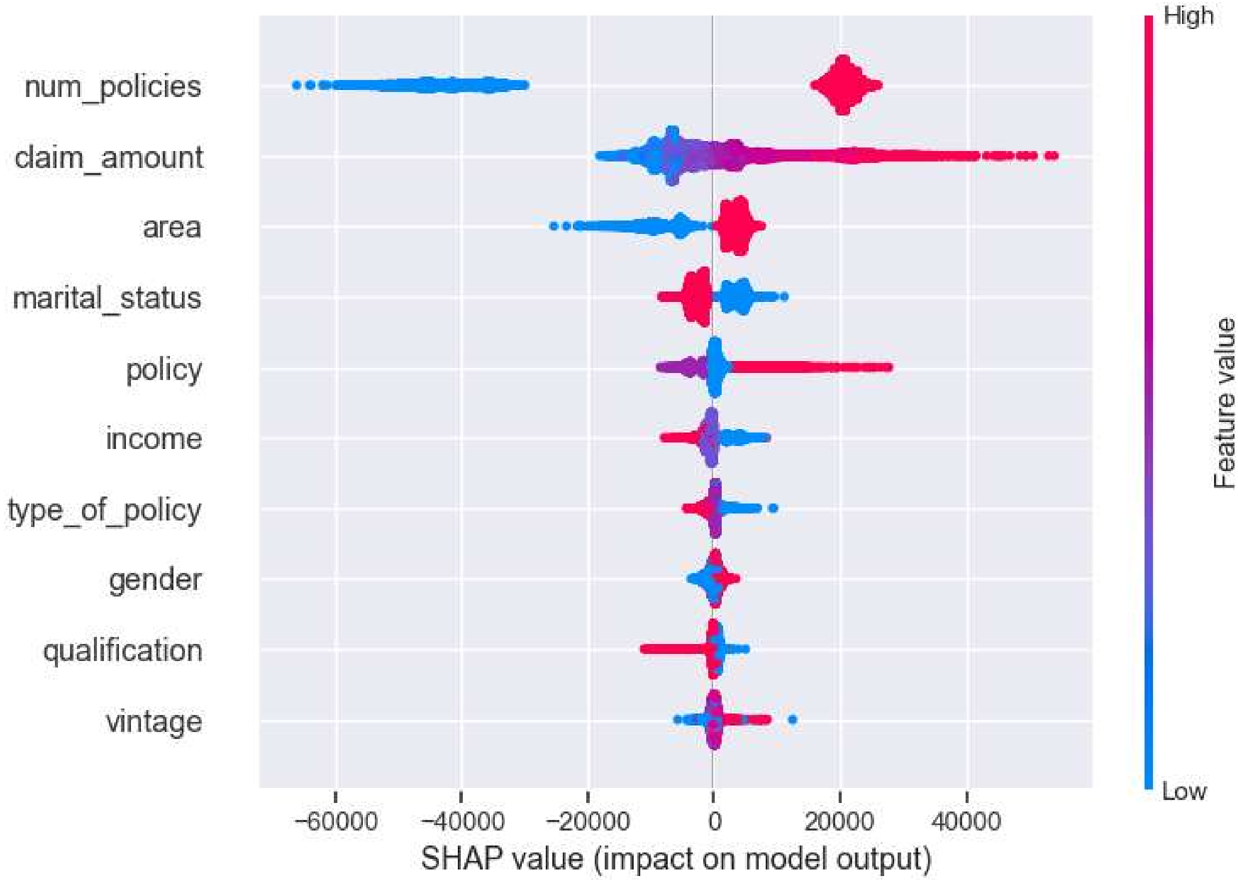
In [25]:
```
from sklearn import metrics
from sklearn.metrics import mean_absolute_percentage_error
import math
y_pred = rf.predict(X_test)
mae = metrics.mean_absolute_error(y_test, y_pred)
mape = mean_absolute_percentage_error(y_test, y_pred)
mse = metrics.mean_squared_error(y_test, y_pred)
r2 = metrics.r2_score(y_test, y_pred)
rmse = math.sqrt(mse)

print('MAE is {}'.format(mae))
print('MAPE is {}'.format(mape))
print('MSE is {}'.format(mse))
print('R2 score is {}'.format(r2))
print('RMSE score is {}'.format(rmse))
```

```
MAE is 50384.94184188802
MAPE is 0.5481493137596379
MSE is 6833618298.871373
R2 score is 0.163775994355433
RMSE score is 82665.70207087927
```

In [26]:
```
imp_df = pd.DataFrame({
    "Feature Name": X_train.columns,
    "Importance": dtree.feature_importances_
})
fi = imp_df.sort_values(by="Importance", ascending=False)

fi2 = fi.head(10)
plt.figure(figsize=(10,8))
sns.barplot(data=fi2, x='Importance', y='Feature Name')
plt.title('Feature Importance Each Attributes (Random Forest Regressor)', fontsize=18)
plt.xlabel ('Importance', fontsize=16)
plt.ylabel ('Feature Name', fontsize=16)
plt.show()
```



In [27]:
```
import shap
explainer = shap.TreeExplainer(rf)
shap_values = explainer.shap_values(X_test)
shap.summary_plot(shap_values, X_test)
```



In [28]:
```
explainer = shap.Explainer(rf, X_test, check_additivity=False)
shap_values = explainer(X_test, check_additivity=False)
shap.plots.waterfall(shap_values[0])
```

```
100%|===================| 17817/17879 [03:54<00:00]
```