Estimation of obesity levels based on eating habits and physical condition - DataTalks.Club's midterm project by Alexander D. Rios

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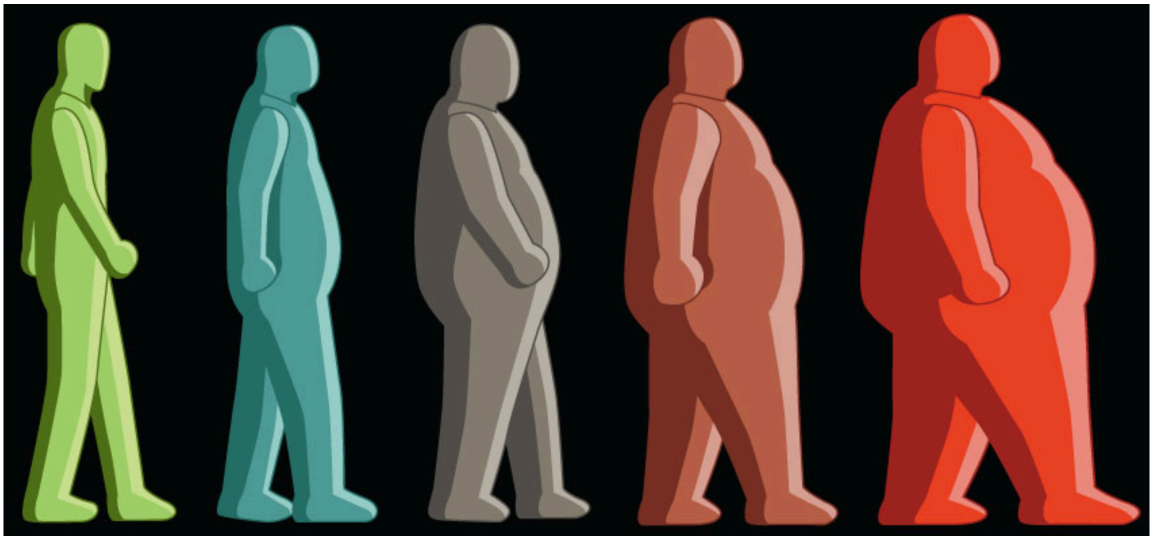


Obesity is a global problem, and an individual's eating habits and physical condition can provide insights into their health status. Poor eating habits and a lack of physical activity can lead to severe obesity, which may have fatal consequences.

In this project, I used data on individuals from Colombia, Peru, and Mexico obtained from the UC Irvine Machine Learning Repository. The dataset contains 17 attributes and 2,111 records, with each record labeled using the class variable `NObesity` (Obesity Level). This variable categorizes obesity levels into the following classes:

- Insufficient Weight
- Normal Weight
- Overweight Level I
- Overweight Level II
- Obesity Type I
- Obesity Type II
- Obesity Type III

Seventy-seven percent of the data was generated synthetically using the Weka tool with the SMOTE filter, while 23% was collected directly from users via a web platform.

Downloading the dataset

In [5]:
```
!wget https://archive.ics.uci.edu/static/public/544/estimation+of+obesity+le
!unzip -o /content/estimation+of+obesity+levels+based+on+eating+habits+and+p
```

```
--2024-11-25 14:16:53--  https://archive.ics.uci.edu/static/public/544/estima
tion+of+obesity+levels+based+on+eating+habits+and+physical+condition.zip
Resolving archive.ics.uci.edu (archive.ics.uci.edu)... 128.195.10.252
Connecting to archive.ics.uci.edu (archive.ics.uci.edu)|128.195.10.252|:44
3... connected.
HTTP request sent, awaiting response... 200 OK
Length: unspecified
Saving to: ‘estimation+of+obesity+levels+based+on+eating+habits+and+physical+
condition.zip’

estimation+of+obesi     [ <=>                  ]  56.32K  --.-KB/s    in 0.1s

2024-11-25 14:16:53 (433 KB/s) - ‘estimation+of+obesity+levels+based+on+eatin
g+habits+and+physical+condition.zip’ saved [57676]

Archive:  /content/estimation+of+obesity+levels+based+on+eating+habits+and+ph
ysical+condition.zip
  inflating: ObesityDataSet_raw_and_data_sinthetic.csv
```

Installing some packages

In [56]:
```
!pip install mplcyberpunk
!pip install catboost

from IPython.display import clear_output

clear_output(wait=False)
```

Feature description

Feature	Description
Gender	
Age	
Height	
Weight	
family_history_with_overweight	Has a family member suffered or suffers from overweight?
FAVC	Do you eat high caloric food frequently?
FCVC	Do you usually eat vegetables in your meals?
NCP	How many main meals do you have daily?
CAEC	Do you eat any food between meals?

SMOKE	Do you smoke?
CH20	How much water do you drink daily?
SCC	Do you monitor the calories you eat daily?
FAF	How often do you have physical activity?
TUE	How much time do you use technological devices such as cell phone, videogames, television, computer and others?
CALC	How often do you drink alcohol?
MTRANS	Which transportation do you usually use?
NObeyesdad	Obesity level

Loading the dataset

In [7]:

```
import pandas as pd
df_raw = pd.read_csv("/content/ObesityDataSet_raw_and_data_sinthetic.csv")
df_raw.head()
```

Out[7]:

	Gender	Age	Height	Weight	family_history_with_overweight	FAVC	FCVC	NCP	
0	Female	21.0	1.62	64.0	yes	no	2.0	3.0	Son
1	Female	21.0	1.52	56.0	yes	no	3.0	3.0	Son
2	Male	23.0	1.80	77.0	yes	no	2.0	3.0	Son
3	Male	27.0	1.80	87.0	no	no	3.0	3.0	Son
4	Male	22.0	1.78	89.8	no	no	2.0	1.0	Son

Exploratory data analysis (EDA)

Renaming the columns

In [8]:

```
df_raw = df_raw.rename(columns={"family_history_with_overweight": "overweigh
                       "FAVC":"eat_HC_food",
                       "FCVC":"eat_vegetables",
                       "NCP":"main_meals",
                       "CAEC":"snack",
                       "CH2O":"drink_water",
                       "SCC":"monitoring_calories",
                       "FAF":"physical_activity",
                       "TUE":"use_of_technology",
                       "CALC":"drink_alcohol",
                       "MTRANS":"transportation_type",
                       "NObeyesdad":"obesity_level"
```

```
                              }).rename(columns=str.lower)
df_raw.columns
```

Out[8]:

```
Index(['gender', 'age', 'height', 'weight', 'overweight_familiar',
       'eat_hc_food', 'eat_vegetables', 'main_meals', 'snack', 'smoke',
       'drink_water', 'monitoring_calories', 'physical_activity',
       'use_of_technology', 'drink_alcohol', 'transportation_type',
       'obesity_level'],
      dtype='object')
```

Dropping duplicated

In [9]:

```
df_raw.duplicated().sum()
```

Out[9]:

```
24
```

In [10]:

```
df_raw = df_raw.drop_duplicates()
df_raw.duplicated().sum()
```

Out[10]:

```
0
```

Looking for missing values

In [11]:

```
df_raw.isna().sum()
```

Out [11]:

	0
gender	0
age	0
height	0
weight	0
overweight_familiar	0
eat_hc_food	0
eat_vegetables	0
main_meals	0
snack	0
smoke	0
drink_water	0
monitoring_calories	0
physical_activity	0
use_of_technology	0
drink_alcohol	0
transportation_type	0
obesity_level	0

dtype: int64

Statistical description

In [12]:

```
df_raw.describe(include="all").T
```

Out[12]:

	count	unique	top	freq	mean	std	min
gender	2087	2	Male	1052	NaN	NaN	NaN
age	2087.0	NaN	NaN	NaN	24.35309	6.368801	14.0
height	2087.0	NaN	NaN	NaN	1.702674	0.093186	1.45
weight	2087.0	NaN	NaN	NaN	86.85873	26.190847	39.0
overweight_familiar	2087	2	yes	1722	NaN	NaN	NaN
eat_hc_food	2087	2	yes	1844	NaN	NaN	NaN
eat_vegetables	2087.0	NaN	NaN	NaN	2.421466	0.534737	1.0
main_meals	2087.0	NaN	NaN	NaN	2.701179	0.764614	1.0
snack	2087	4	Sometimes	1761	NaN	NaN	NaN
smoke	2087	2	no	2043	NaN	NaN	NaN
drink_water	2087.0	NaN	NaN	NaN	2.004749	0.608284	1.0
monitoring_calories	2087	2	no	1991	NaN	NaN	NaN
physical_activity	2087.0	NaN	NaN	NaN	1.012812	0.853475	0.0
use_of_technology	2087.0	NaN	NaN	NaN	0.663035	0.608153	0.0
drink_alcohol	2087	4	Sometimes	1380	NaN	NaN	NaN
transportation_type	2087	5	Public_Transportation	1558	NaN	NaN	NaN
obesity_level	2087	7	Obesity_Type_I	351	NaN	NaN	NaN

Looking for the classes in categorical features

In [13]:
```
df_raw.head()
```

Out[13]:

	gender	age	height	weight	overweight_familiar	eat_hc_food	eat_vegetables	main_
0	Female	21.0	1.62	64.0	yes	no	2.0	
1	Female	21.0	1.52	56.0	yes	no	3.0	
2	Male	23.0	1.80	77.0	yes	no	2.0	
3	Male	27.0	1.80	87.0	no	no	3.0	
4	Male	22.0	1.78	89.8	no	no	2.0	

In [14]:
```
df_raw.select_dtypes("object").nunique()
```

Out [14]:

	0
gender	2
overweight_familiar	2
eat_hc_food	2
snack	4
smoke	2
monitoring_calories	2
drink_alcohol	4
transportation_type	5
obesity_level	7

dtype: int64

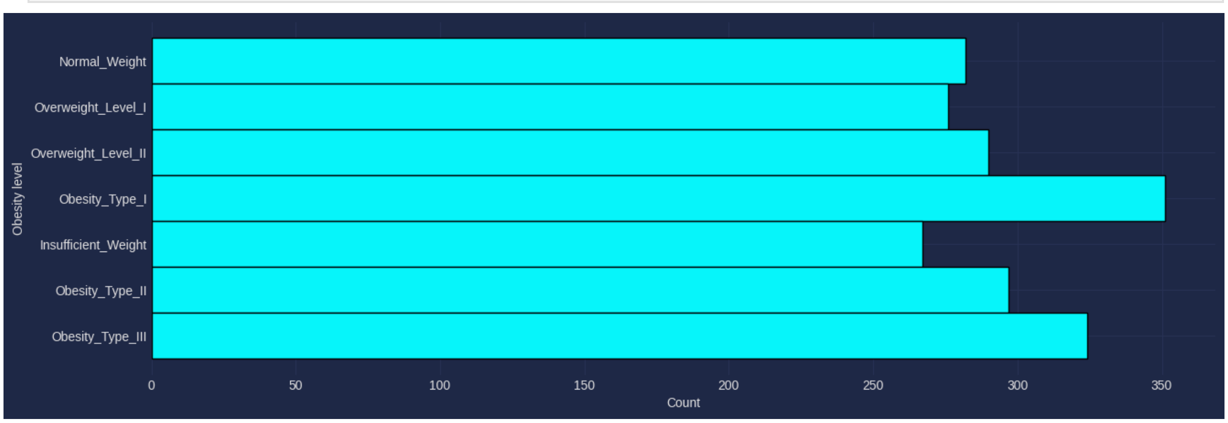
In [15]:
```
df = df_raw.copy()
```

Data visualization

In [16]:
```
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import mplcyberpunk

plt.style.use("cyberpunk")
```

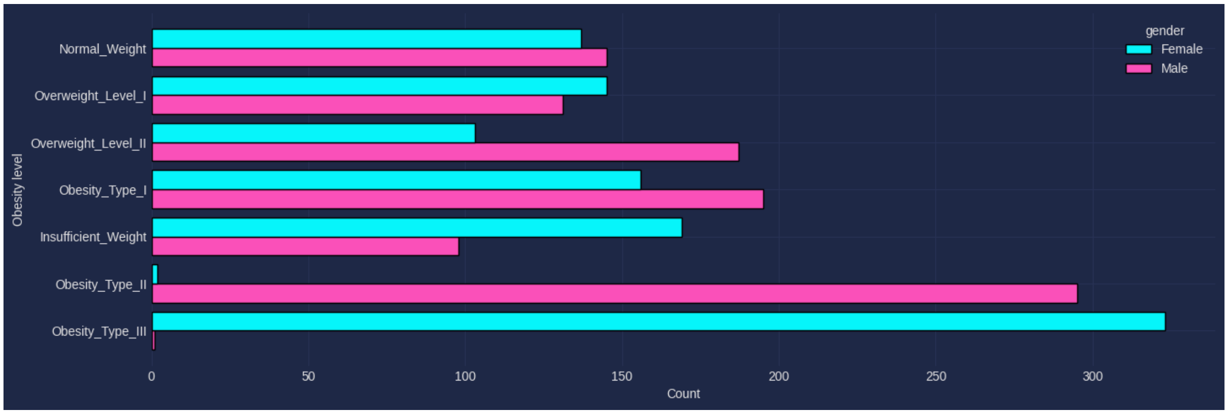
Balance of the target variable

In [17]:
```
plt.figure(figsize=(15, 5))
sns.histplot(df, y="obesity_level", alpha=1)
plt.ylabel("Obesity level");
```



The relationship between obesity levels and the gender

In [18]:
```
plt.figure(figsize=(15, 5))
sns.histplot(df, y="obesity_level", hue="gender", multiple="dodge", shrink=0
plt.ylabel("Obesity level");
```



The balance in the gender feature:

In [19]:
```
df.gender.value_counts(normalize=True)
```

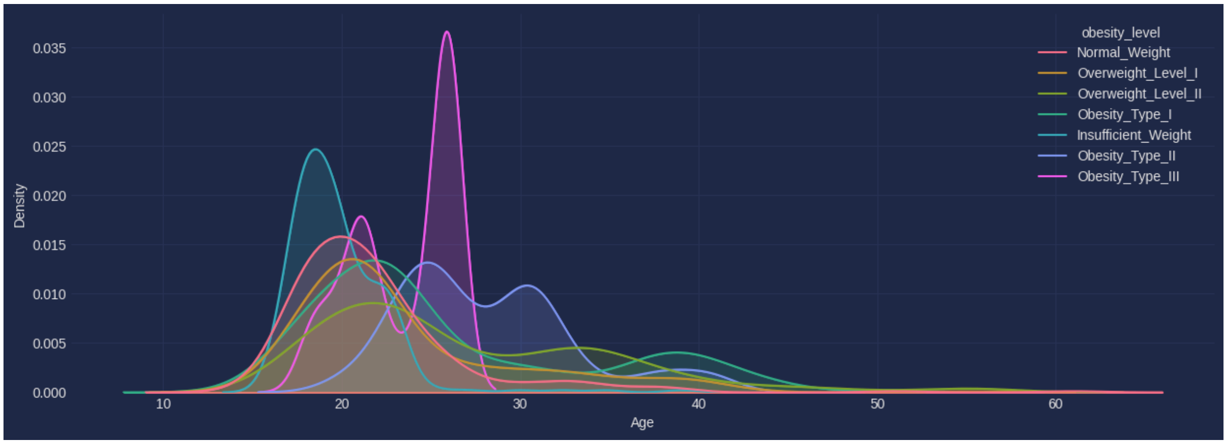
Out[19]:

	proportion
gender	
Male	0.504073
Female	0.495927

dtype: float64

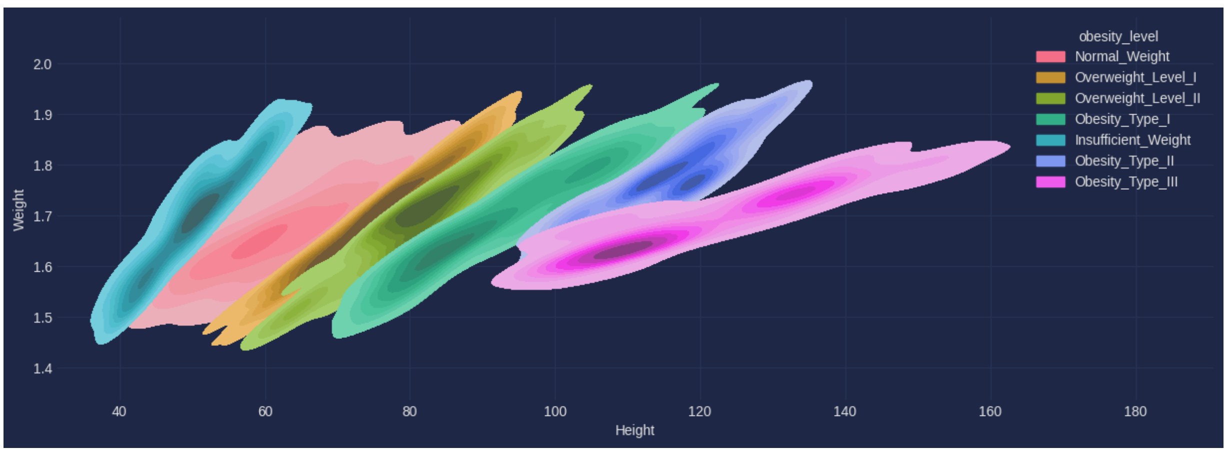
The distribution of age in relation to obesity levels

In [20]:
```
plt.figure(figsize=(15, 5))
sns.kdeplot(df, x="age", hue="obesity_level", fill=True, alpha=.2)
sns.kdeplot(df, x="age", hue="obesity_level")
plt.xlabel("Age");
```



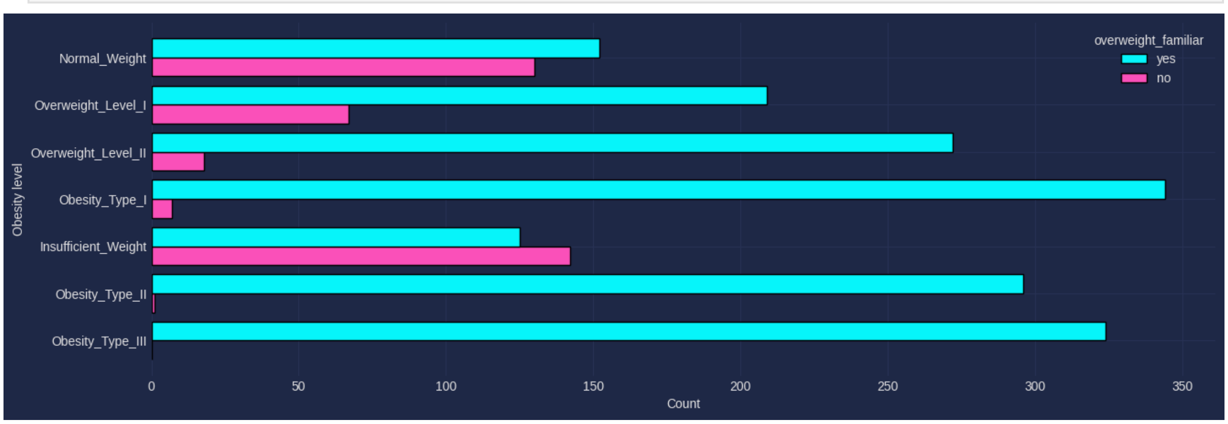
Height and weight in relation to obesity levels

In [21]:
```
plt.figure(figsize=(15, 5))
sns.kdeplot(data=df, x="weight", y="height", hue="obesity_level", fill=True)
plt.xlabel("Height")
plt.ylabel("Weight");
```



The relationship between obesity levels and having overweight family members

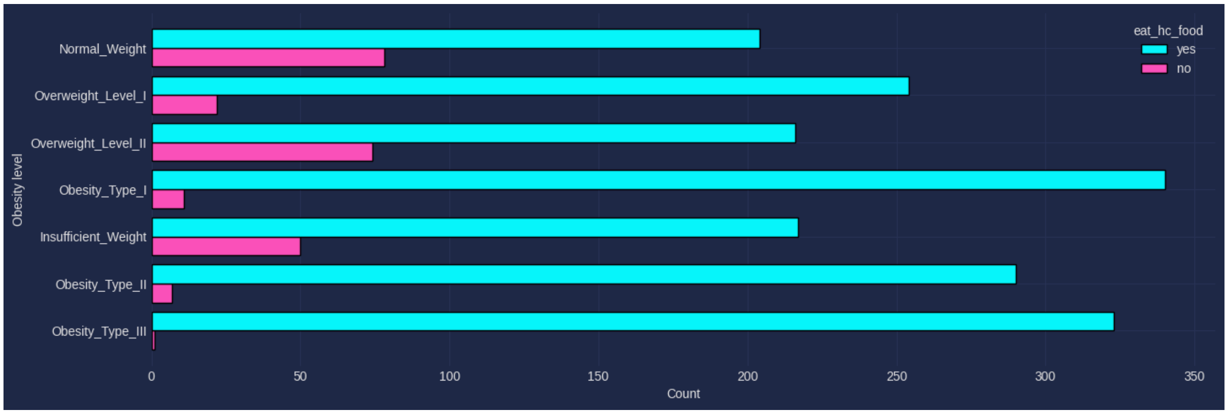
In [22]:
```
plt.figure(figsize=(15, 5))
sns.histplot(df, y="obesity_level", hue="overweight_familiar", multiple="dod
plt.ylabel("Obesity level");
```



The relationship between obesity levels and the consumption of high-calorie foods

In [23]:

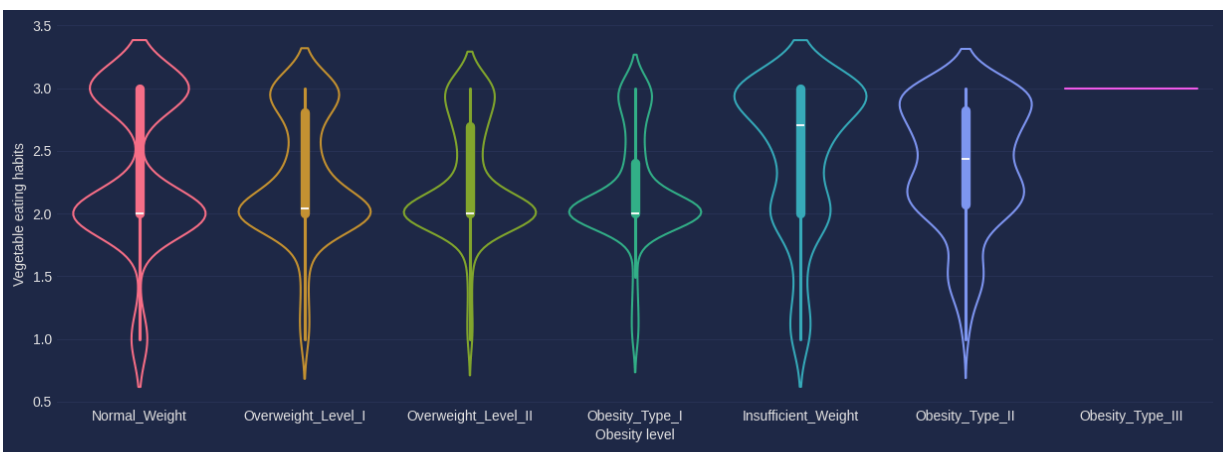
```
plt.figure(figsize=(15, 5))
sns.histplot(df, y="obesity_level", hue="eat_hc_food", multiple="dodge", shr
plt.ylabel("Obesity level");
```



The relationship between obesity levels and vegetable eating habits

In [24]:

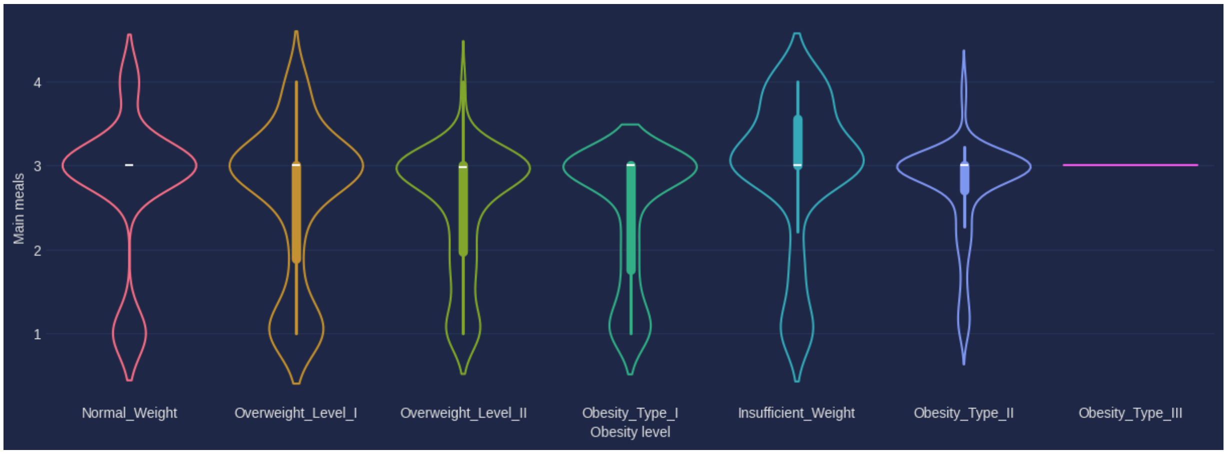
```
plt.figure(figsize=(15, 5))
sns.violinplot(data=df, x="obesity_level", y="eat_vegetables", hue="obesity_
plt.ylabel("Vegetable eating habits")
plt.xlabel("Obesity level");
```



The relationship between obesity levels and the number of main meals

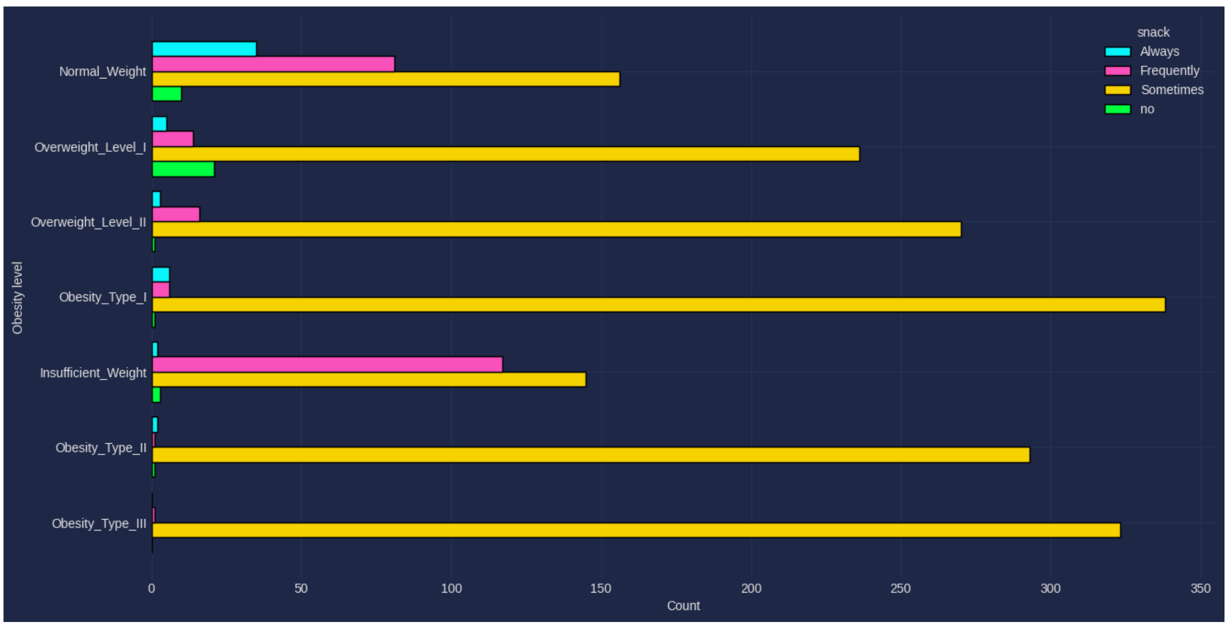
In [25]:

```
plt.figure(figsize=(15, 5))
sns.violinplot(data=df, x="obesity_level", y="main_meals", hue="obesity_leve
plt.ylabel("Main meals")
plt.xlabel("Obesity level");
```



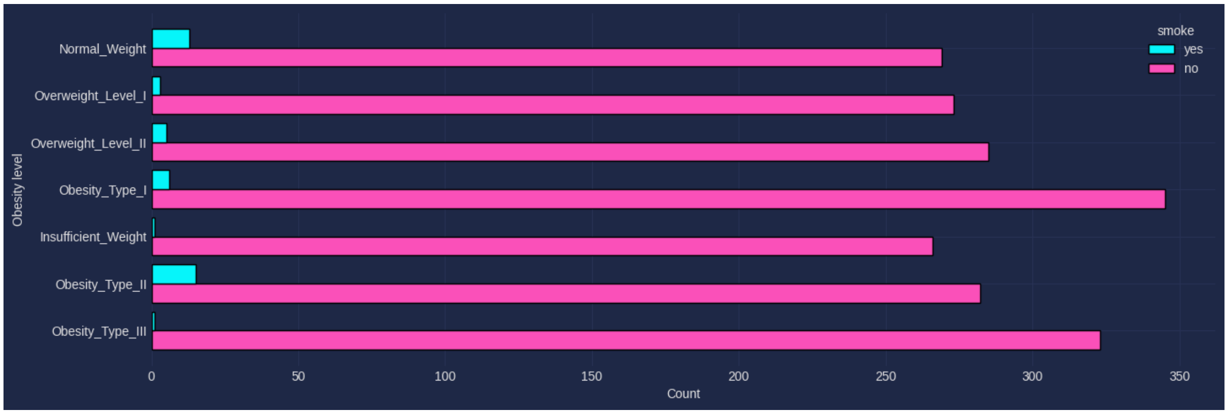
The relationship between obesity levels and snack eating habits

In [26]:
```
plt.figure(figsize=(15, 8))
sns.histplot(df, y="obesity_level", hue="snack", multiple="dodge", shrink=0.
plt.ylabel("Obesity level");
```



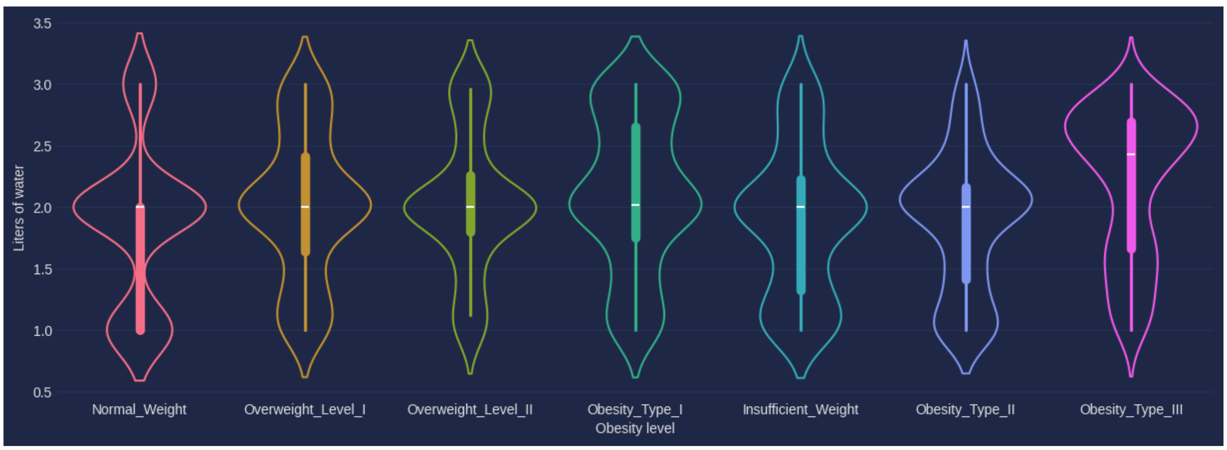
The relationship between obesity levels and smoking habits

In [27]:
```
plt.figure(figsize=(15, 5))
sns.histplot(df, y="obesity_level", hue="smoke", multiple="dodge", shrink=0.
plt.ylabel("Obesity level");
```



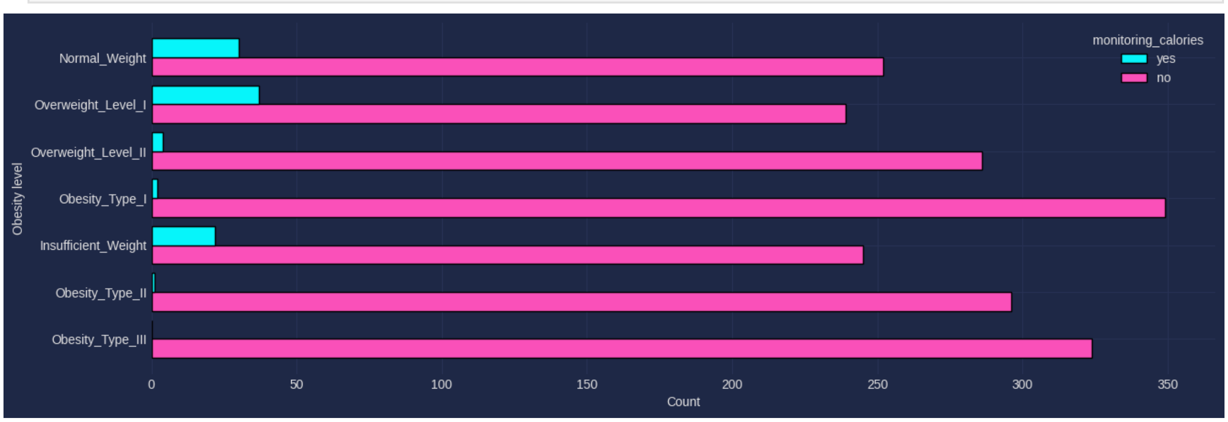
The relationship between obesity levels and water consumption

In [28]:
```
plt.figure(figsize=(15, 5))
sns.violinplot(data=df, x="obesity_level", y="drink_water", hue="obesity_lev
plt.ylabel("Liters of water")
plt.xlabel("Obesity level");
```



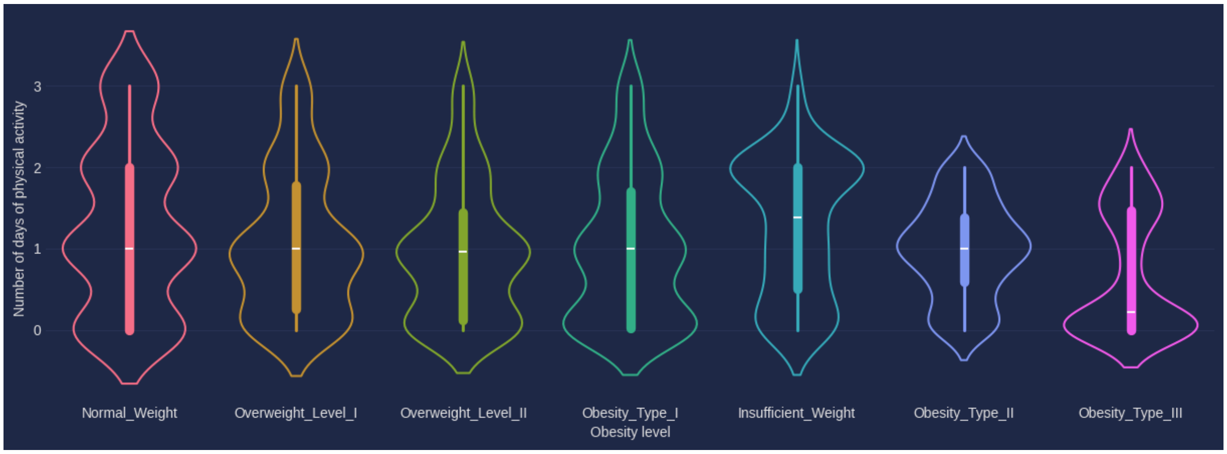
Calorie monitoring habits in relation to obesity levels

In [29]:
```
plt.figure(figsize=(15, 5))
sns.histplot(df, y="obesity_level", hue="monitoring_calories", multiple="dod
plt.ylabel("Obesity level");
```



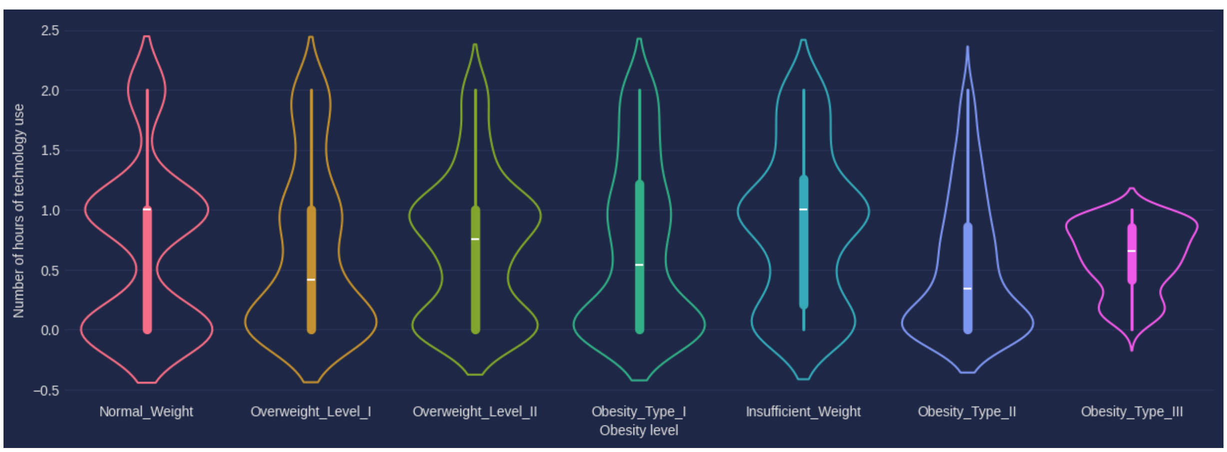
Physical activity in relation to obesity levels

In [30]:
```
plt.figure(figsize=(15, 5))
sns.violinplot(data=df, x="obesity_level", y="physical_activity", hue="obesi
plt.ylabel("Number of days of physical activity")
plt.xlabel("Obesity level");
```



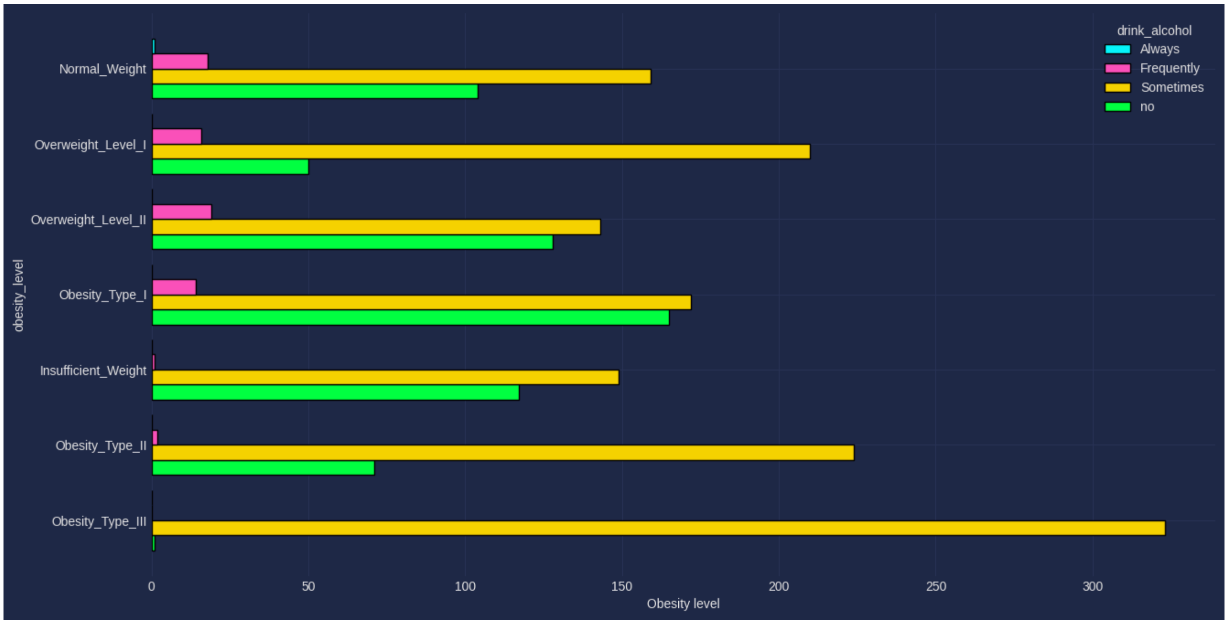
Technology usage habits in relation to obesity levels

In [31]:
```
plt.figure(figsize=(15, 5))
sns.violinplot(data=df, x="obesity_level", y="use_of_technology", hue="obesi
plt.ylabel("Number of hours of technology use")
plt.xlabel("Obesity level");
```



Alcohol drinking habits in relation to obesity levels

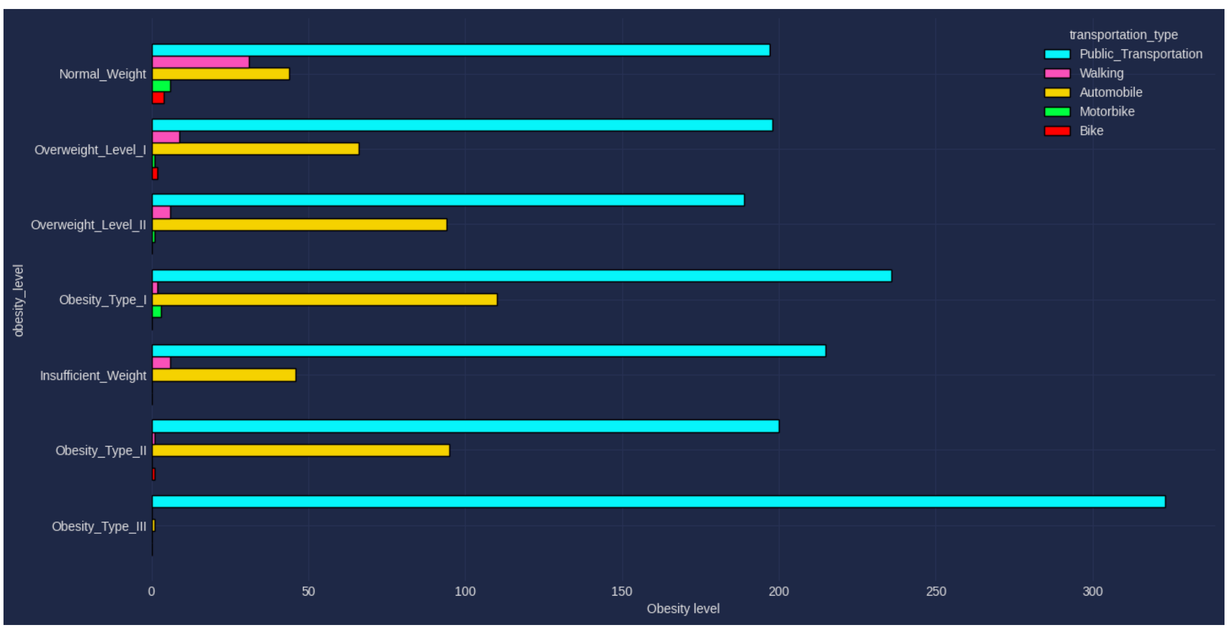
In [32]:
```
plt.figure(figsize=(15, 8))
sns.histplot(df, y="obesity_level", hue="drink_alcohol", multiple="dodge", s
plt.xlabel("Obesity level");
```



Obesity levels according to the type of transportation used

In [33]:

```
plt.figure(figsize=(15, 8))
sns.histplot(df, y="obesity_level", hue="transportation_type", multiple="dod
plt.xlabel("Obesity level");
```



Splitting the dataset

Setting seeds for reproducibility

In [34]:

```
import random
import os
import keras
```

```
seed_value = 42
os.environ['PYTHONHASHSEED'] = str(seed_value)
random.seed(seed_value)
np.random.seed(seed_value)
```

Setting the validation framework

In [35]:
```
from sklearn.model_selection import train_test_split

df_full_train, df_test = train_test_split(df, test_size=0.15, random_state=s
df_train, df_val = train_test_split(df_full_train, test_size=0.15, random_st
len(df_train), len(df_test), len(df_val)
```

Out[35]:
```
(1507, 314, 266)
```

Removing specific columns and separating features from the target column

According to the dataset's article, the data was labeled using the following equation:

$$Mass\ body\ index = \frac{weight}{height^2}$$

Therefore, we need to delete at least a feature into previous equation.

In [36]:
```
cols_drop = ["obesity_level", "weight"]
X_full_train, y_full_train = df_full_train.drop(cols_drop, axis=1), df_full_
X_train, y_train =  df_train.drop(cols_drop, axis=1), df_train["obesity_leve
X_val, y_val =  df_val.drop(cols_drop, axis=1), df_val["obesity_level"]
X_test, y_test =  df_test.drop(cols_drop, axis=1), df_test["obesity_level"]
```

Standardization

In [37]:
```
from sklearn.preprocessing import StandardScaler

numeric_cols = X_train.select_dtypes(exclude=["object"]).columns

ss = StandardScaler().set_output(transform="pandas")

ss.fit(X_train[numeric_cols])
ss.transform(X_train[numeric_cols])
```

Out [37]:

	age	height	eat_vegetables	main_meals	drink_water	physical_activity	us
2071	-0.859706	0.482798	1.091725	0.378982	0.667080	-0.024754	
190	-0.679409	-1.084919	-0.803418	0.378982	-0.005343	-0.007330	
1361	-0.996350	-0.153529	0.593585	0.378982	-0.009926	0.410323	
2109	0.011829	0.409630	1.091725	0.378982	1.387169	0.157412	
325	-0.520938	-1.620791	-0.803418	-2.235837	-1.639098	-0.007330	
...	...	...	...	...	...	...	
1357	-0.996350	0.891401	-0.803418	-0.306828	1.066065	-0.007330	
1013	4.906080	0.729214	-0.803418	0.378982	-0.005343	-0.007330	
1971	-0.790813	1.243673	1.091725	0.378982	1.137754	0.609467	
1265	-1.048027	0.399074	-0.803418	0.378982	-0.005343	-1.191614	
1881	0.029785	-0.069697	1.091725	0.378982	1.177656	-0.792753	

1507 rows × 7 columns

One-hot encoding of features

In [38]:

```
from sklearn.feature_extraction import DictVectorizer

dict_X_full_train = X_full_train.to_dict("records")
dict_X_train = X_train.to_dict("records")
dict_X_val = X_val.to_dict("records")
dict_X_test = X_test.to_dict("records")

dv = DictVectorizer(sparse=False).set_output(transform="pandas")
dv.fit(dict_X_train)

dv.transform(dict_X_train).head()
```

Out [38]:

	age	drink_alcohol=Always	drink_alcohol=Frequently	drink_alcohol=Sometimes	(
0	18.862264	0.0	0.0	1.0	
1	20.000000	0.0	0.0	1.0	
2	18.000000	0.0	0.0	1.0	
3	24.361936	0.0	0.0	1.0	
4	21.000000	0.0	0.0	1.0	

5 rows × 30 columns

Creating a Pipeline

In [39]:
```
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import Pipeline

class MyStandardScaler(BaseEstimator, TransformerMixin):
    def __init__(self, numeric_cols):
        self.ss = StandardScaler().set_output(transform="pandas")
        self.numeric_cols = numeric_cols
        return

    def fit(self, X):
        self.ss.fit(X[self.numeric_cols])
        return self

    def transform(self, X):
        X[self.numeric_cols] = self.ss.transform(X[self.numeric_cols])
        return X.to_dict("records")

numeric_cols = X_train.select_dtypes(exclude=["object"]).columns
pipe = Pipeline([('ss', MyStandardScaler(numeric_cols=numeric_cols)), ('dv',

X_train = pipe.fit_transform(X_train)
X_full_train = pipe.transform(X_full_train)
X_val = pipe.transform(X_val)
X_test = pipe.transform(X_test)
```

Label encoding

In [40]:
```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
le.fit(y_train)
y_full_train = le.transform(y_full_train)
y_train = le.transform(y_train)
y_val = le.transform(y_val)
y_test = le.transform(y_test)
```

Computing weigths for classes and samples

In [41]:
```
from sklearn.utils.class_weight import compute_sample_weight, compute_class_

class_full_weight = compute_class_weight(class_weight="balanced", classes=np
class_full_weight = dict(zip(np.unique(y_full_train), class_full_weight))

class_weight = compute_class_weight(class_weight="balanced", classes=np.uniq
class_weight = dict(zip(np.unique(y_train), class_weight))

sample_full_weights = compute_sample_weight(
```

```
    class_weight=class_full_weight,
    y=y_full_train
)

sample_weights = compute_sample_weight(
    class_weight=class_weight,
    y=y_train
)
```

Training the models

Logistic Regression

In [42]:
```
from sklearn.metrics import roc_auc_score
```

In [ ]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

parameters = {"max_iter":[200, 300, 400, 500],
              "C":[20, 15, 10],
              "class_weight":["balanced"],
              "solver":["lbfgs", "newton-cg", "sag", "saga"]}

lr = LogisticRegression(random_state=seed_value)
gs_lr = GridSearchCV(lr, param_grid=parameters, n_jobs=-1, cv=5, scoring="ro
gs_lr.fit(X_full_train, y_full_train, sample_weight=sample_full_weights)
```

```
/usr/local/lib/python3.10/dist-packages/numpy/ma/core.py:2820: RuntimeWarnin
g: invalid value encountered in cast
  _data = np.array(data, dtype=dtype, copy=copy,
```

Out[ ]:
```
▸ GridSearchCV
▸ best_estimator_: LogisticRegression
    ▸ LogisticRegression
```

In [ ]:
```
y_pred_test_lr = gs_lr.predict_proba(X_test)
roc_auc_score(y_test, y_pred_test_lr, multi_class="ovr")
```

Out[ ]:
```
0.889393203661662
```

Decision Tree

In [ ]:
```
from sklearn.tree import DecisionTreeClassifier
parameters = {"criterion":["gini", "entropy", "log_loss"],
              "max_depth":[5, 6, 7, 8, 9],
              "max_leaf_nodes":[30, 40, 50, 60],
              "min_samples_split":[30, 40],
```

```
                "class_weight":["balanced"],}

dt = DecisionTreeClassifier(random_state=seed_value)
gs_dt = GridSearchCV(dt, param_grid=parameters, n_jobs=-1, cv=5, scoring="ro
gs_dt.fit(X_full_train, y_full_train, sample_weight=sample_full_weights)
```

Out[ ]:

```
GridSearchCV
best_estimator_: DecisionTreeClassifier
DecisionTreeClassifier
```

In [ ]:

```
y_pred_test_dt = gs_dt.predict_proba(X_test)
roc_auc_score(y_test, y_pred_test_dt, multi_class="ovr")
```

Out[ ]: 0.9213027545513881

Random Forest

In [ ]:

```
from sklearn.ensemble import RandomForestClassifier
parameters = {"criterion":["gini", "entropy", "log_loss"],
                "n_estimators":[100, 200, 300, 400],
                "max_depth":[5, 6, 7, 8, 9],
                "class_weight":["balanced"],}

rf = RandomForestClassifier(random_state=seed_value)
gs_rf = GridSearchCV(rf, param_grid=parameters, n_jobs=-1, cv=5, scoring="ro
gs_rf.fit(X_full_train, y_full_train, sample_weight=sample_full_weights)
```

```
/usr/local/lib/python3.10/dist-packages/numpy/ma/core.py:2820: RuntimeWarnin
g: invalid value encountered in cast
  _data = np.array(data, dtype=dtype, copy=copy,
```

Out[ ]:

```
GridSearchCV
best_estimator_: RandomForestClassifier
RandomForestClassifier
```

In [ ]:

```
y_pred_test_rf = gs_rf.predict_proba(X_test)
roc_auc_score(y_test, y_pred_test_rf, multi_class="ovr")
```

Out[ ]: 0.9721096055019289

Gradient Boosting with XGBoost

In [55]:

```
import xgboost as xgb

dtrain = xgb.DMatrix(X_train, label=y_train, feature_names=X_train.columns.t
```

```
dval = xgb.DMatrix(X_val, label=y_val, feature_names=X_val.columns.tolist())
dtest = xgb.DMatrix(X_test, label=y_test, feature_names=X_test.columns.tolis

xgb_params = {
    'eta': 0.1,
    'max_depth': 6,
    'gamma':0.0001,
    'min_child_weight': 1,
    'alpha':0.01,

    'objective': 'multi:softprob',
    'num_class':7,
    'nthread': 8,
    'eval_metric':'auc',
    'num_parallel_tree':5,

    'seed':seed_value,
    'verbosity': 1,
}

watchlist = [(dtrain, 'train'), (dval, 'val')]
xgb_clf = xgb.train(xgb_params, dtrain, num_boost_round=10000, early_stoppin
y_test_pred_xgb = xgb_clf.predict(dtest)
print(f"ROC:{roc_auc_score(y_test, y_test_pred_xgb, multi_class='ovr')}")
```

```
[0]	train-auc:0.96308	val-auc:0.88976
[200]	train-auc:1.00000	val-auc:0.97088
[400]	train-auc:1.00000	val-auc:0.97176
[600]	train-auc:1.00000	val-auc:0.97269
[800]	train-auc:1.00000	val-auc:0.97309
[942]	train-auc:1.00000	val-auc:0.97303
ROC:0.9806772041514711
```

Gradient Boosting with CatBoost

According to this blog.

CatBoost operates on the principle of gradient boosting, where it builds the model in a stage-wise fashion. It starts with a simple model and incrementally improves it by adding new models that correct the errors made by the preceding ones.

CatBoost introduces several key innovations:

Ordered Boosting

One of the core innovations of CatBoost is its ordered boosting mechanism. Traditional gradient boosting methods can suffer from prediction shift due to the overlap between the training data for the base models and the data used to calculate the gradients. CatBoost addresses this by introducing a random permutation of the dataset in each iteration and using only the data before each example in the permutation for training. This approach reduces overfitting and improves model robustness.

Symmetric Trees

CatBoost builds balanced trees, also known as symmetric trees, as its base predictors. Unlike traditional gradient boosting methods that build trees leaf-wise or depth-wise, CatBoost's symmetric trees ensure that all leaf nodes at the same level share the same decision rule. This leads to faster execution and reduces the likelihood of overfitting.

In [53]:

```python
from catboost import CatBoostClassifier

cbc = CatBoostClassifier(loss_function='MultiClass',
                         eval_metric='AUC',
                         iterations=5000,
                         depth=6,
                         classes_count=7,
                         class_weights=class_weight,
                         learning_rate=0.1,
                         od_type='Iter',
                         early_stopping_rounds=1000,
                         bootstrap_type='MVS',
                         sampling_frequency='PerTree',
                         random_seed=seed_value,
                         verbose=200)
cbc.fit(X_train, y_train, sample_weight=sample_weights, eval_set=(X_val, y_va

y_test_pred_cbc = cbc.predict_proba(X_test)
print(f"ROC:{roc_auc_score(y_test, y_test_pred_cbc, multi_class='ovr')}")
```

```
0:      test: 0.8701799 best: 0.8701799 (0)     total: 36.5ms   remaining: 6m
5s
200:    test: 0.9843814 best: 0.9843814 (200)   total: 6.27s    remaining: 5m
5s
400:    test: 0.9859230 best: 0.9860489 (384)   total: 9.02s    remaining: 3m
35s
600:    test: 0.9859990 best: 0.9862174 (434)   total: 11.7s    remaining: 3m
2s
800:    test: 0.9860843 best: 0.9865136 (706)   total: 14.4s    remaining: 2m
45s
1000:   test: 0.9861372 best: 0.9865136 (706)   total: 19s      remaining: 2m
51s
1200:   test: 0.9859280 best: 0.9865136 (706)   total: 21.9s    remaining: 2m
40s
1400:   test: 0.9860076 best: 0.9865136 (706)   total: 24.5s    remaining: 2m
30s
1600:   test: 0.9857638 best: 0.9865136 (706)   total: 27.2s    remaining: 2m
22s
Stopped by overfitting detector  (1000 iterations wait)

bestTest = 0.9865136358
bestIteration = 706

Shrink model to first 707 iterations.
ROC:0.9849353946292636
```

Neural Networks

In [ ]:
```
import tensorflow as tf
from tensorflow.data import Dataset
from tensorflow.keras import Input, Model
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.losses import SparseCategoricalCrossentropy
from tensorflow.keras.optimizers import Adamax
from tensorflow.keras.metrics import SparseCategoricalAccuracy
```

In [ ]:
```
tf.keras.backend.clear_session()
keras.utils.set_random_seed(seed_value)

autotune = tf.data.AUTOTUNE

batch_size = 32

train_data = Dataset.from_tensor_slices((X_train.astype(float), y_train.astyp
val_data = Dataset.from_tensor_slices((X_val.astype(float), y_val.astype(float
test_data = Dataset.from_tensor_slices((X_test.astype(float), y_test.astype(fl

early = EarlyStopping(monitor='val_loss', patience=10)

inp = Input(shape=(30, ))
x = Dense(256, activation='relu')(inp)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
x = Dense(128, activation='relu')(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
x = Dense(7, activation='softmax')(x)

nn = Model(inputs=inp, outputs=x)
nn.compile(loss=SparseCategoricalCrossentropy(), optimizer=Adamax(learning_r
nn.summary()
```

Model: "functional"

Layer (type)	Output Shape
input_layer (InputLayer)	(None, 30)
dense (Dense)	(None, 256)
dense_1 (Dense)	(None, 128)
dropout (Dropout)	(None, 128)
dense_2 (Dense)	(None, 128)
dense_3 (Dense)	(None, 128)
dropout_1 (Dropout)	(None, 128)
dense_4 (Dense)	(None, 7)

Total params: 74,759 (292.03 KB)

Trainable params: 74,759 (292.03 KB)

Non-trainable params: 0 (0.00 B)

In [ ]:

```
epochs = 1000
history = nn.fit(train_data,
                epochs=epochs,
                verbose=1,
                validation_data=val_data,
                class_weight=class_weight,
                callbacks=[early]
                )
```

```
Epoch 1/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 3s 8ms/step - loss: 1.8327 - sparse_categorical_a
ccuracy: 0.2595 - val_loss: 1.2738 - val_sparse_categorical_accuracy: 0.4511
Epoch 2/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 1.3165 - sparse_categorical_a
ccuracy: 0.4592 - val_loss: 1.0407 - val_sparse_categorical_accuracy: 0.6617
Epoch 3/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 1.1631 - sparse_categorical_a
ccuracy: 0.5468 - val_loss: 0.9571 - val_sparse_categorical_accuracy: 0.6692
Epoch 4/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 1.0944 - sparse_categorical_a
ccuracy: 0.5979 - val_loss: 0.9358 - val_sparse_categorical_accuracy: 0.6654
Epoch 5/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.9901 - sparse_categorical_a
ccuracy: 0.6048 - val_loss: 0.9158 - val_sparse_categorical_accuracy: 0.6617
Epoch 6/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.9382 - sparse_categorical_a
ccuracy: 0.6409 - val_loss: 0.8158 - val_sparse_categorical_accuracy: 0.6992
Epoch 7/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.8868 - sparse_categorical_a
ccuracy: 0.6698 - val_loss: 0.8139 - val_sparse_categorical_accuracy: 0.7293
Epoch 8/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.7843 - sparse_categorical_a
ccuracy: 0.7220 - val_loss: 0.7592 - val_sparse_categorical_accuracy: 0.7556
Epoch 9/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.7551 - sparse_categorical_a
ccuracy: 0.7096 - val_loss: 0.7370 - val_sparse_categorical_accuracy: 0.7406
Epoch 10/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.7274 - sparse_categorical_a
ccuracy: 0.7371 - val_loss: 0.7488 - val_sparse_categorical_accuracy: 0.7519
Epoch 11/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.6668 - sparse_categorical_a
ccuracy: 0.7442 - val_loss: 0.7169 - val_sparse_categorical_accuracy: 0.7744
Epoch 12/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.6312 - sparse_categorical_a
ccuracy: 0.7730 - val_loss: 0.7175 - val_sparse_categorical_accuracy: 0.7895
Epoch 13/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.6090 - sparse_categorical_a
ccuracy: 0.7854 - val_loss: 0.7165 - val_sparse_categorical_accuracy: 0.7782
Epoch 14/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.5573 - sparse_categorical_a
ccuracy: 0.8115 - val_loss: 0.7084 - val_sparse_categorical_accuracy: 0.8045
Epoch 15/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.5673 - sparse_categorical_a
ccuracy: 0.7960 - val_loss: 0.7481 - val_sparse_categorical_accuracy: 0.7895
Epoch 16/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.5021 - sparse_categorical_a
ccuracy: 0.8189 - val_loss: 0.7435 - val_sparse_categorical_accuracy: 0.7632
Epoch 17/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.4850 - sparse_categorical_a
ccuracy: 0.8306 - val_loss: 0.7140 - val_sparse_categorical_accuracy: 0.8083
Epoch 18/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.4586 - sparse_categorical_a
ccuracy: 0.8487 - val_loss: 0.7559 - val_sparse_categorical_accuracy: 0.8045
Epoch 19/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.4490 - sparse_categorical_a
```

```
ccuracy: 0.8545 - val_loss: 0.8031 - val_sparse_categorical_accuracy: 0.8083
Epoch 20/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.4681 - sparse_categorical_a
ccuracy: 0.8568 - val_loss: 0.7520 - val_sparse_categorical_accuracy: 0.8083
Epoch 21/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.4161 - sparse_categorical_a
ccuracy: 0.8657 - val_loss: 0.7829 - val_sparse_categorical_accuracy: 0.7970
Epoch 22/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.4019 - sparse_categorical_a
ccuracy: 0.8610 - val_loss: 0.8005 - val_sparse_categorical_accuracy: 0.7932
Epoch 23/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.4139 - sparse_categorical_a
ccuracy: 0.8593 - val_loss: 0.8020 - val_sparse_categorical_accuracy: 0.7932
Epoch 24/1000
48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - loss: 0.3586 - sparse_categorical_a
ccuracy: 0.8893 - val_loss: 0.8445 - val_sparse_categorical_accuracy: 0.7970
```

In [ ]:
```
y_pred_test_nn = nn.predict(test_data, batch_size=batch_size)

roc_auc_score(y_test, y_pred_test_nn, multi_class='ovr')
```

```
10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 9ms/step
```

Out[ ]:
```
0.9612609703428328
```

Comparison of models

In [ ]:
```
from sklearn.metrics import f1_score, accuracy_score, precision_score, recal

def get_scores(y_true, y_pred, y_pred_proba):
    return {'AUC_ROC':roc_auc_score(y_true, y_pred_proba, multi_class='ovr')
            'F1_Score':f1_score(y_true, y_pred, average='weighted'),
            'Accuracy':accuracy_score(y_true, y_pred),
            'Precision':precision_score(y_true, y_pred, average='weighted'),
            'Recall':recall_score(y_true, y_pred, average='weighted')}
scores = []
for model in [gs_lr, gs_dt, gs_rf, xgb_clf, cbc, nn]:
    if model == xgb_clf:
        y_test_pred = np.argmax(model.predict(dtest), axis=1)
        y_test_pred_proba = model.predict(dtest)
    elif model == nn:
        y_test_pred = np.argmax(model.predict(test_data), axis=1)
        y_test_pred_proba = model.predict(test_data)
    else:
        y_test_pred = model.predict(X_test)
        y_test_pred_proba = model.predict_proba(X_test)
    scores.append(get_scores(y_test, y_test_pred, y_test_pred_proba).values(

comparison = pd.DataFrame(data=scores, index=["Logistic Regression", "Decisi
comparison.style.highlight_max(color = 'green', axis = 0).highlight_min(colo
```

```
10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
```

Out[ ]:

	AUC_ROC	F1_Score	Accuracy	Precision	Recall
Logistic Regression	0.889393	0.621080	0.636943	0.631468	0.636943
Decision Tree	0.921303	0.682760	0.681529	0.691372	0.681529
Random Forest	0.972110	0.838787	0.840764	0.842998	0.840764
XGBoost	0.980677	0.866181	0.866242	0.867547	0.866242
CatBoost	0.984935	0.891044	0.891720	0.891502	0.891720
Neural Network	0.961261	0.831495	0.831210	0.835182	0.831210

Confusion matrix

In [ ]:

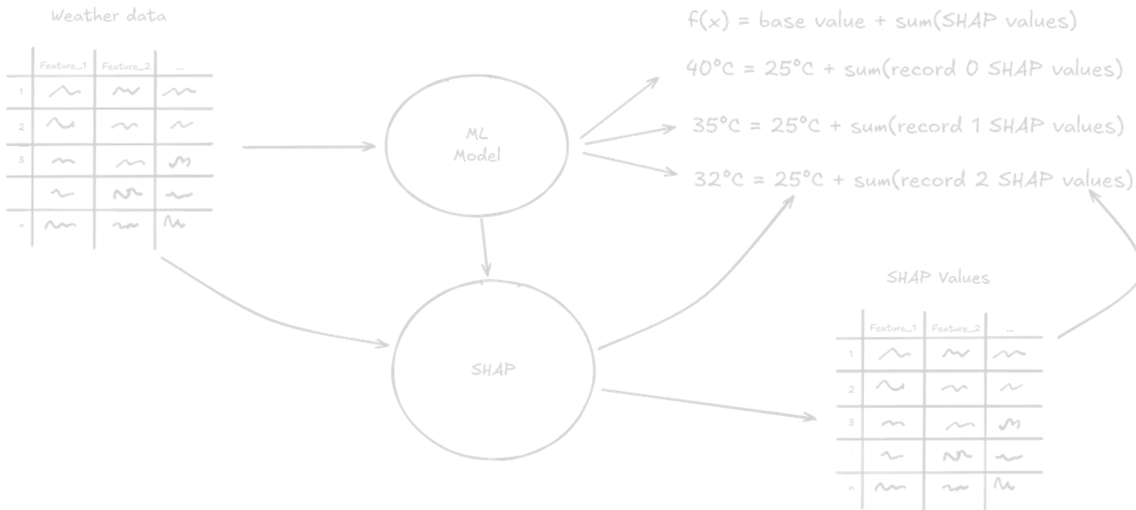
```
from sklearn.metrics import confusion_matrix

def my_cm(y_true, y_pred, title):
    cm_val = confusion_matrix(y_true, y_pred)
    cm_pgs = np.round(confusion_matrix(y_true, y_pred, normalize='true')*100

    formatted_text = (np.asarray([f"{pgs}%\n({val})" for val, pgs in zip(cm_

    sns.heatmap(cm_pgs, annot=formatted_text, fmt='', cmap='BuPu', yticklabe
    plt.title(title)
    plt.xlabel("Prediction")
    plt.ylabel("Expected")

    plt.subplots_adjust(hspace=0.5)
    return

y_test_pred_cbc = cbc.predict(X_test)

plt.figure(figsize=(10, 10))
my_cm(y_test, y_test_pred_cbc, title="Catboost")
```

Feature importance analysis with SHAP

SHAP is a method that explains how individual predictions are made by a machine learning model. SHAP deconstructs a prediction into a sum of contributions from each of the model's input variables. For each instance in the data, the contribution from each input variable towards the model's prediction will vary depending on the values of the variables for that particular instance.

A machine learning model's prediction, f(x), can be represented as the sum of its computed SHAP values, plus a fixed base value, such that:

$$f(x) = base\ value + SUM(SHAP\ values)$$



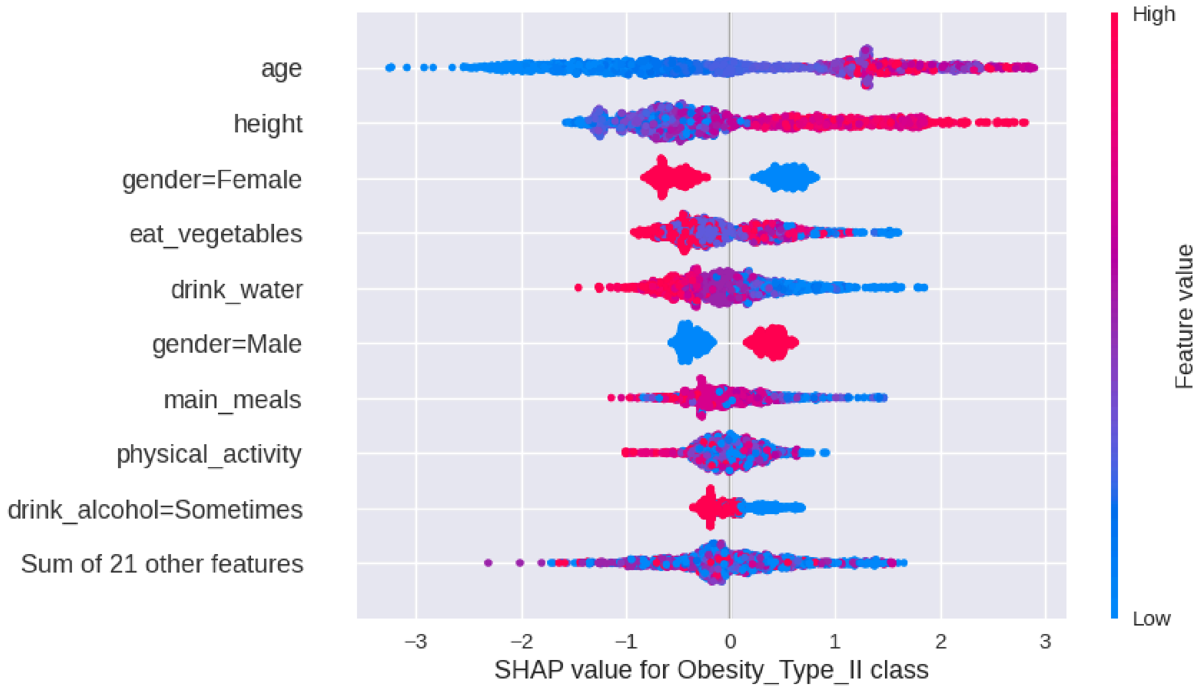
In [ ]:
```
import shap

shap.initjs()
```

In [ ]:
```
explainer = shap.TreeExplainer(cbc)
shap_values = explainer(X_train, y_train)
```

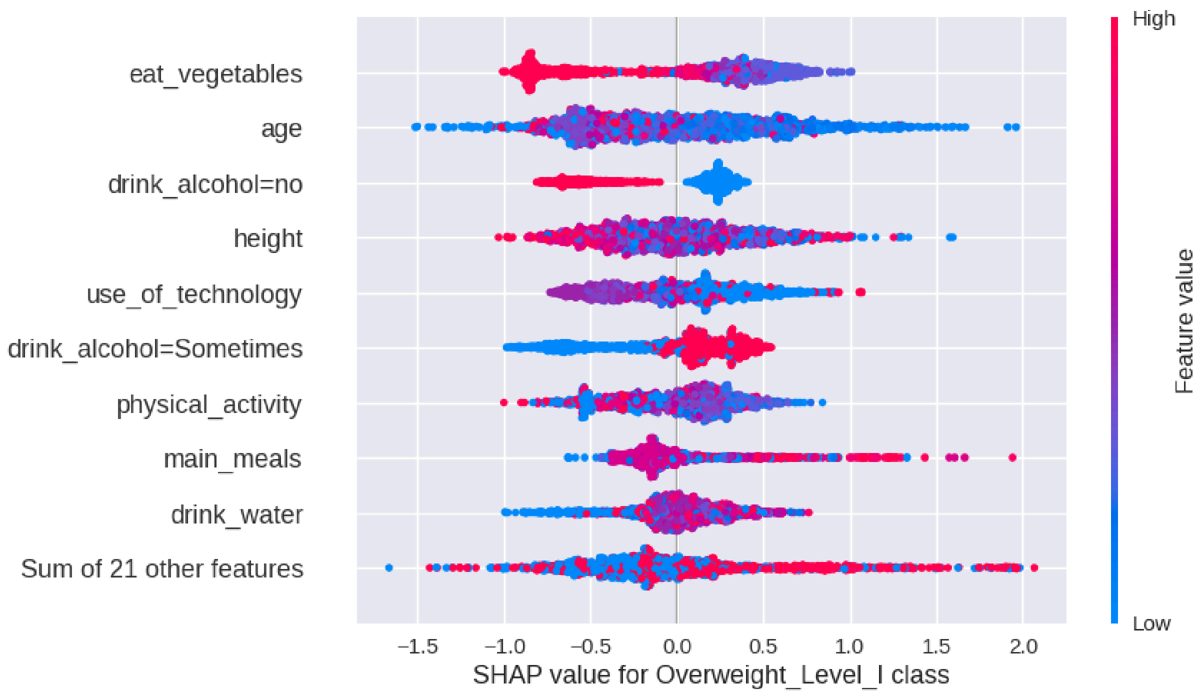
In [ ]:
```
plt.style.use("seaborn-v0_8")
for i in range(6):
    shap.plots.beeswarm(shap_values[..., i], show=False)
    plt.xlabel(f"SHAP value for {le.classes_[i]} class")
    plt.show()
```

height
drink_water
age
eat_vegetables
use_of_technology
physical_activity
main_meals
overweight_familiar=yes
overweight_familiar=no
Sum of 21 other features
−2
−1
0
1
2
3
SHAP value for Normal_Weight class
High
Low
Feature value

eat_vegetables
age
height
drink_water
main_meals
use_of_technology
overweight_familiar=yes
physical_activity
overweight_familiar=no
Sum of 21 other features
−2
−1
0
1
2
SHAP value for Obesity_Type_I class
High
Low
Feature value


age
height
gender=Female
eat_vegetables
drink_water
gender=Male
main_meals
physical_activity
drink_alcohol=Sometimes
Sum of 21 other features
−3
−2
−1
0
1
2
3
SHAP value for Obesity_Type_II class
High
Feature value
Low


eat_vegetables
gender=Female
gender=Male
drink_alcohol=Sometimes
age
main_meals
height
use_of_technology
drink_water
Sum of 21 other features
−2
−1
0
1
2
SHAP value for Obesity_Type_III class
High
Feature value
Low



According to the diagram presented above, when a point (an instance) is blue, it indicates that its original feature value in the dataset is low, whereas when a point is red, it indicates that the original feature value in the dataset is high.

With this clarified, four situations can arise:

- Red point scattered towards negative SHAP values: For this instance, the feature indicates that the higher its value, the lower the prediction value, as it requires the SHAP value contribution to the prediction to be smaller.
- Red point scattered towards positive SHAP values: On the contrary, for this instance, the feature indicates that the higher its value, the higher the prediction value, as it requires the SHAP value contribution to the prediction to be larger.
- Blue point scattered towards negative SHAP values: For this instance, the feature indicates that the lower its value, the lower the prediction value, as it requires the SHAP value contribution to the prediction to be smaller.
- Blue point scattered towards positive SHAP values: For this instance, the feature indicates that the lower its value, the higher the prediction value, as it requires the SHAP value contribution to the prediction to be larger.

In this way, we can conclude that, for example, for the Insufficient_Weight class, the individual's age, the higher it is, the less likely it is that this individual belongs to this class. On the other hand, it can be seen that for the Normal_Weight class, it is more likely that individuals who belong to this class have high physical activity.

Saving the pipeline, the label encoder and the model with CloudPickle

An important difference between `cloudpickle` and `pickle` is that `cloudpickle` can serialize a function or class **by value**, whereas `pickle` can only serialize it **by reference**.

Serialization by reference treats functions and classes as attributes of modules, and pickles them through instructions that trigger the import of their module at load time. **Serialization by reference** is thus limited in that it assumes that the module containing the function or class is available/importable in the unpickling environment. This assumption breaks when pickling constructs defined in an interactive session, a case that is automatically detected by `cloudpickle`, that pickles such constructs **by value**.

In [ ]:
```
import cloudpickle

with open('obesity-levels-model.bin', 'wb') as f_out:
    cloudpickle.dump((pipe, le, cbc), f_out)
```

Converting Notebook to PDF

In [1]:
```
!apt-get install texlive-xetex texlive-fonts-recommended texlive-plain-gener
!pip install pypandoc nbconvert[webpdf]
!playwright install

from google.colab import drive
from IPython.display import clear_output
drive.mount('/content/drive')
clear_output(wait=False)
```

In [4]:
```
%%capture
!jupyter nbconvert --to webpdf /content/drive/MyDrive/ML_Zoomcamps_2024/Midt
```