Machine Learning with the Experts: School Budgets

1). Exploring the raw data:

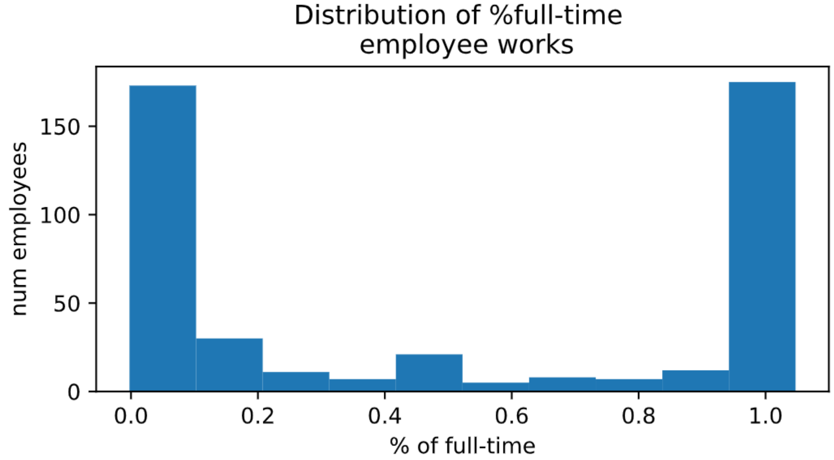
a). Summarizing the Data

```
# Print the summary statistics
print(df.describe())

# Import matplotlib.pyplot as plt
import matplotlib.pyplot as plt

# Create the histogram
plt.hist(df['FTE'].dropna())

# Add title and labels
plt.title('Distribution of %full-time \n employee works')
plt.xlabel('% of full-time')
plt.ylabel('num employees')
# Display the histogram
plt.show()
```



b). <u>Encode the labels as Categorical Values</u>

```
# Define the lambda function: categorize_label
categorize_label = lambda x: x.astype('category')

# Convert df[LABELS] to a categorical type
df[LABELS] = df[LABELS].apply(categorize_label, axis=0)

# Print the converted dtypes
print(df[LABELS].dtypes)
```

<script.py> output:

```
Function            category
Use                 category
Sharing             category
Reporting           category
Student_Type        category
Position_Type       category
Object_Type         category
Pre_K               category
Operating_Status    category
dtype: object
```

c). Counting Unique Labels

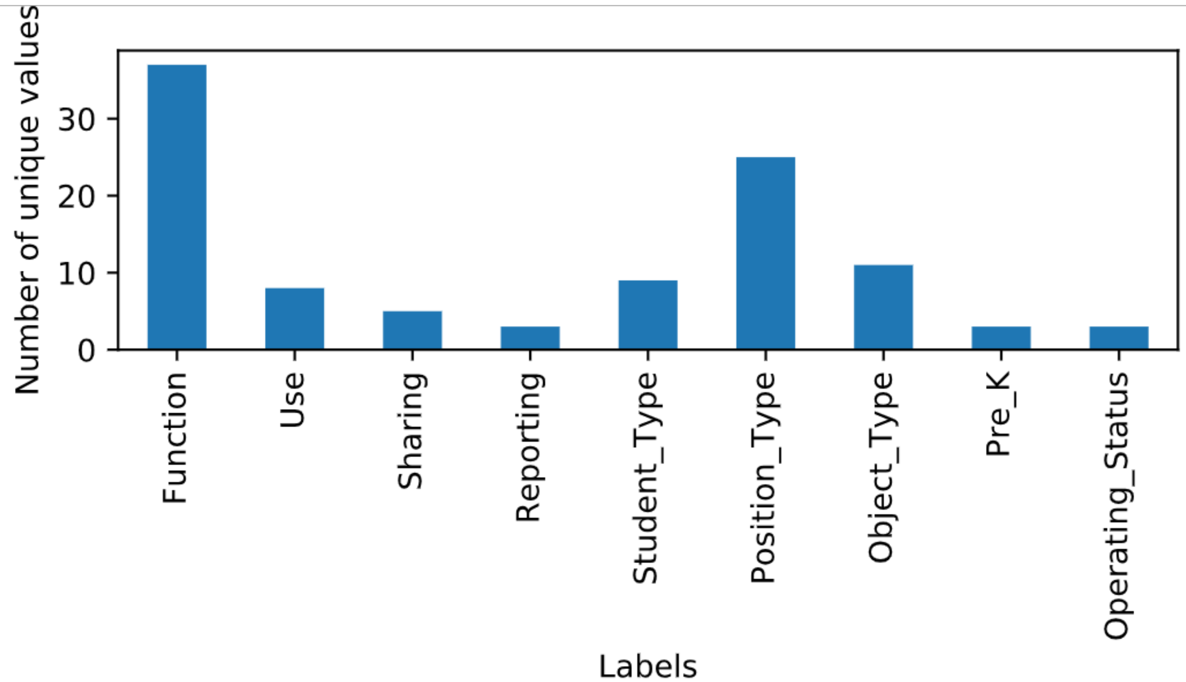
```
# Import matplotlib.pyplot
import matplotlib.pyplot as plt

# Calculate number of unique values for each label: num_unique_labels
num_unique_labels = df[LABELS].apply(pd.Series.nunique)

# Plot number of unique values for each label
num_unique_labels.plot(kind='bar')

# Label the axes
plt.xlabel('Labels')
plt.ylabel('Number of unique values')

# Display the plot
plt.show()
```



d). <u>Computing logloss with numpy</u>

```
# Compute and print log loss for 1st case
correct_confident = compute_log_loss(correct_confident, actual_labels)
print("Log loss, correct and confident: {}".format(correct_confident))

# Compute log loss for 2nd case
correct_not_confident = compute_log_loss(correct_not_confident, actual_labels)
print("Log loss, correct and not confident: {}".format(correct_not_confident))

# Compute and print log loss for 3rd case
wrong_not_confident = compute_log_loss(wrong_not_confident, actual_labels)
print("Log loss, wrong and not confident: {}".format(wrong_not_confident))

# Compute and print log loss for 4th case
wrong_confident = compute_log_loss(wrong_confident, actual_labels)
print("Log loss, wrong and confident: {}".format(wrong_confident))

# Compute and print log loss for actual labels
actual_labels = compute_log_loss(actual_labels, actual_labels)
print("Log loss, actual labels: {}".format(actual_labels))
```

<script.py> output:

```
    Log loss, correct and confident: 0.05129329438755058
    Log loss, correct and not confident: 0.4307829160924542
    Log loss, wrong and not confident: 1.049822124498678
    Log loss, wrong and confident: 2.9957322735539904
    Log loss, actual labels: 9.99200722162646e-15
```