```
import requests
import pandas as pd
from collections import Counter
import pandas as pd
import plotly.express as px
```

Reading The Dataset

```
url = "https://api.github.com/repos/rails/rails/issues"
issues = []

params = {
    "state": "all",
    "per_page": 100,
}

for i in range(1, 6):
    params["page"] = i
    response = requests.get(url, params=params)
    issues.extend(response.json())

df = pd.DataFrame(issues)
```

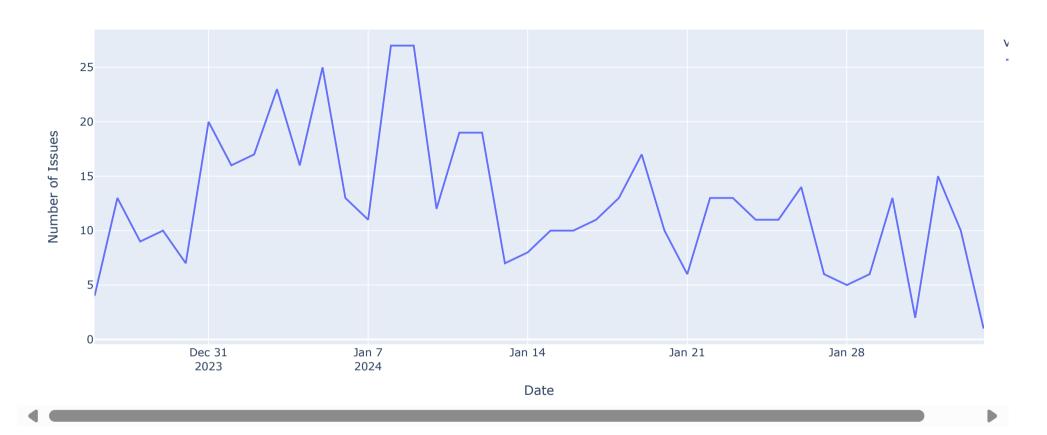
	url	repository_url	labels_url			
0	https://api.github.com/repos/rails/rails/issue	https://api.github.com/repos/rails/rails	https://api.github.com/repos/rails/rails/issue	https://api.github.co		
1	https://api.github.com/repos/rails/rails/issue	https://api.github.com/repos/rails/rails	https://api.github.com/repos/rails/rails/issue	https://api.github.co		
2	https://api.github.com/repos/rails/rails/issue	https://api.github.com/repos/rails/rails	https://api.github.com/repos/rails/rails/issue	https://api.github.co		
3	https://api.github.com/repos/rails/rails/issue	https://api.github.com/repos/rails/rails	https://api.github.com/repos/rails/rails/issue	https://api.github.co		
4	https://api.github.com/repos/rails/rails/issue	https://api.github.com/repos/rails/rails	https://api.github.com/repos/rails/rails/issue	https://api.github.co		
5 rows × 30 columns						

→ 1. How do the number of issues evolve over time?

```
df['created_at'] = pd.to_datetime(df['created_at'])
issue_counts_by_date = df.resample('D', on='created_at').size()

# Plot
fig = px.line(issue_counts_by_date, title='Number of Issues Over Time')
fig.update_xaxes(title_text='Date')
fig.update_yaxes(title_text='Number of Issues')
fig.show()
```

Number of Issues Over Time



2. Are there any periods in which we get more issues?

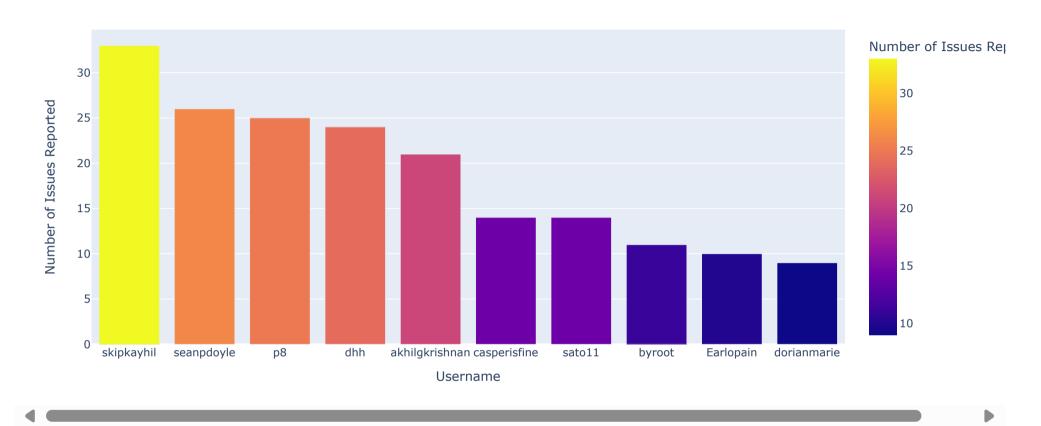
Yes, there are distinct periods where more issues are reported. These periods are represented by the peaks in the line chart. Specifically, from the provided image, it appears that:

• There is a significant peak in the number of issues reported around the first week of January 2024. This could indicate a surge in activity, possibly due to new year code sprints, releases, or other community activities. Another noticeable peak occurs in the third week of January 2024, suggesting another period with increased issue reporting.

- The final week of January 2024 also shows an increased number of issues, though not as pronounced as the first peak.
- These peaks could be due to various reasons such as new feature deployments, version updates, or discovery of bugs that coincide with these dates. It would be beneficial to cross-reference these dates with the Rails project's update logs, community forums, or other documentation to understand the context behind the increased number of issues.
- 3. Is there anyone who reports more issues than others?

```
df['reporter'] = df['user'].apply(lambda x: x['login'] if isinstance(x, dict) else None)
top reporters = df['reporter'].value counts().head(10)
print(top reporters)
     skipkayhil
                       33
     seanpdoyle
                       26
     p8
                       25
     dhh
                       24
     akhilgkrishnan
                       21
     casperisfine
     sato11
                       14
     byroot
                       11
     Earlopain
                       10
     dorianmarie
     Name: reporter, dtype: int64
top reporters data = top reporters.reset index()
top reporters data.columns = ['Reporter', 'Frequency']
fig = px.bar(top reporters data, x='Reporter', y='Frequency',
             title='Top Issue Reporters',
             labels={'Reporter': 'Username', 'Frequency': 'Number of Issues Reported'},
             color='Frequency')
fig.show()
```

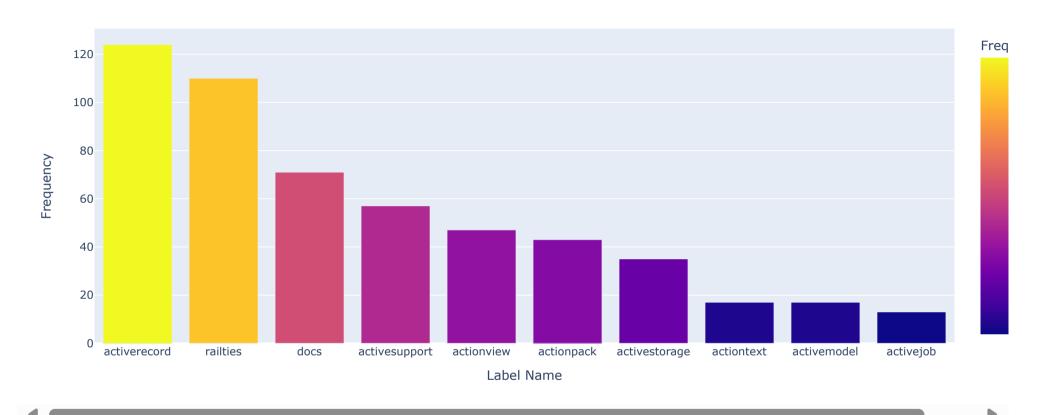
Top Issue Reporters



4. What is the most popular category (label)?

```
def extract label names(labels):
    return [label['name'] for label in labels if 'name' in label]
df['label names'] = df['labels'].apply(extract label names)
all label names = sum(df['label names'].tolist(), [])
label counts = Counter(all label names)
labels frequency df = pd.DataFrame(label counts.items(), columns=['Label Name', 'Frequency']).sort values(by='Frequency', ascending=False).reset
fig = px.bar(labels frequency df.head(10),
            x='Label Name',
            y='Frequency',
            title='Top 10 Most Popular Labels',
             labels={'Label Name': 'Label Name', 'Frequency': 'Frequency'},
             color='Frequency',
fig.update_layout(xaxis_title="Label Name",
                 yaxis title="Frequency",
                 xaxis={'categoryorder':'total descending'}
fig.show()
```

Top 10 Most Popular Labels



Most Discussed Issues

most_discussed_issues = df.sort_values(by='comments', ascending=False)
print(most_discussed_issues[['title', 'comments']].head(10))

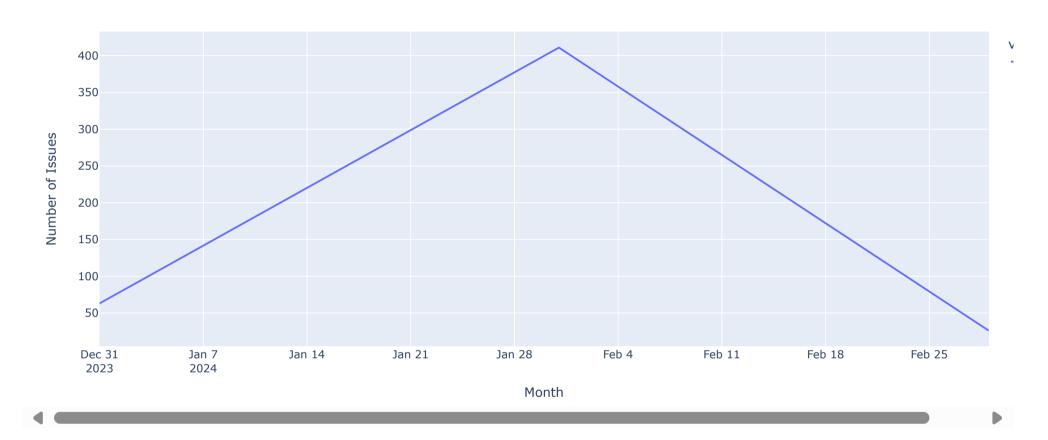
	title	comments
496	Set a new default for the Puma thread count	83
490	Add (a very basic!!) Rubocop by default	30
180	Request: rename Rails console as irr or someth	23
384	Generate devcontainer files by default	20

```
467
              Warning on serialize from ActiveStorage
                                                             13
492
    Extract Action Notifier framework for push not...
                                                             13
                                                             13
439
                   Default to creating git pre-commit
    Add rate limiting to Action Controller via the...
                                                             13
460
            Introduce `ActiveSupport::TestCase.around`
                                                             11
63
471 Add Thruster to Docker setup to get HTTP/2, X-...
                                                             11
```

```
issue_counts_by_month = df.resample('M', on='created_at').size()

# Plot
fig = px.line(issue_counts_by_month, title='Number of Issues Each Month')
fig.update_xaxes(title_text='Month')
fig.update_yaxes(title_text='Number of Issues')
fig.show()
```

Number of Issues Each Month



Classification Task

```
import pandas as pd
import torch
from torch.utils.data import Dataset, DataLoader
from sklearn.model selection import train test split
from transformers import AutoTokenizer, AutoModelForSequenceClassification, AdamW, get linear schedule with warmup, Trainer, TrainingArgument
from sklearn.metrics import accuracy score, precision recall fscore support
import numpy as np
def get first label(label list):
    if label list:
        return label list[0]['name'] # This gets the name of the first label
    else:
        return 'No Label'
df['single_label'] = df['labels'].apply(get_first_label)
# Assuming df is your DataFrame
df['body'] = df['body'].astype(str) # Ensure text column is string
df['single label'] = pd.factorize(df['single label'])[0]
class GitHubIssueDataset(Dataset):
    def init (self, encodings, labels):
        self.encodings = encodings
        self.labels = labels
    def __getitem__(self, idx):
        item = {key: torch.tensor(val[idx]) for key, val in self.encodings.items()}
        item['labels'] = torch.tensor(self.labels[idx])
        return item
    def len (self):
        return len(self.labels)
# Load tokenizer
tokenizer = AutoTokenizer.from pretrained('bert-base-uncased')
# Prepare datasets
X train, X val, y train, y val = train test split(df['body'], df['single label'], test size=0.2)
train encodings = tokenizer(X train.tolist(), truncation=True, padding=True)
val encodings = tokenizer(X val.tolist(), truncation=True, padding=True)
train_dataset = GitHubIssueDataset(train_encodings, y_train.tolist())
```

```
val dataset = GitHubIssueDataset(val encodings, y val.tolist())
# Load model
model = AutoModelForSequenceClassification.from pretrained('bert-base-uncased', num labels=len(df['single label'].unique()))
# Training arguments
training args = TrainingArguments(
    output dir='./results',
    num train epochs=3,
    per device train batch size=8,
    warmup steps=500,
    weight decay=0.01,
    logging_dir='./logs',
    evaluation strategy="epoch",
    logging_steps=10,
    save strategy="epoch",
    load best model at end=True,
# Custom compute metrics function
def compute metrics(pred):
   labels = pred.label ids
    preds = pred.predictions.argmax(-1) # Convert model logits to class predictions
    # Use 'macro', 'micro', or 'weighted' averaging based on your specific needs
    precision, recall, f1, = precision recall fscore support(labels, preds, average='macro')
    acc = accuracy_score(labels, preds)
    return {
        'accuracy': acc,
        'f1': f1,
        'precision': precision,
        'recall': recall
# Initialize Trainer
trainer = Trainer(
    model=model,
    args=training args,
    train dataset=train dataset,
    eval dataset=val dataset,
    compute_metrics=compute_metrics,
```

```
# Train the model
trainer.train()
```