Robot-Run Cafe in Los Angeles

We are contemplating the idea of launching a small cafe in Los Angeles that would be run by robots. To evaluate this venture, we have conducted market research based on open-source data.

Data description

- `rest_data` table:
- `object_name` — establishment name
- `chain` — chain establishment (TRUE/FALSE)
- `object_type` — establishment type
- `address` — address
- `number` — number of seats

Initialization

Installing additional packages:

In [1]:
```
!pip install -qq usaddress
```

Loading libraries:

In [2]:
```
import pandas as pd
import numpy as np
import datetime as dt
from scipy import stats as st
import warnings
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
import matplotlib.ticker as mtick
from matplotlib import ticker
from matplotlib.ticker import PercentFormatter
from matplotlib.ticker import PercentFormatter
from matplotlib.ticker import FuncFormatter
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
import plotly.io as pio
import usaddress
```

In [3]:
```
plt.rcParams["figure.figsize"] = (8, 4)          # matplotlib+seaborn figure size
pio.templates.default = "seaborn"                        # plotly color template (gl
#px.defaults.template = "seaborn"                        # plotly express color temp
pio.renderers.default = 'notebook'
```

```python
pd.set_option("max_colwidth", 300)

warnings.filterwarnings("ignore")
```

Preprocessing

Loading data

In [4]:
```python
rest = pd.read_csv("rest_data_us.csv")
```

`data` table

In [5]:
```python
rest.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9651 entries, 0 to 9650
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   id           9651 non-null   int64 
 1   object_name  9651 non-null   object
 2   address      9651 non-null   object
 3   chain        9648 non-null   object
 4   object_type  9651 non-null   object
 5   number       9651 non-null   int64 
dtypes: int64(2), object(4)
memory usage: 452.5+ KB
```

Checking NAs in `chain`:

In [6]:
```python
rest[rest['chain'].isna()]
```

Out[6]:

	id	object_name	address	chain	object_type	number
7408	19194	TAQUERIA LOS 3 CARNALES	5000 E WHITTIER BLVD	NaN	Restaurant	14
7523	19309	JAMMIN JIMMY'S PIZZA	1641 FIRESTONE BLVD	NaN	Pizza	1
8648	20434	THE LEXINGTON THEATER	129 E 3RD ST	NaN	Restaurant	35

These restaurants don't belong to chains. Filling NAs with `False`

In [7]:
```python
rest['chain'].fillna(False, inplace=True)
```

In [8]:
```python
rest.describe()
```

Out[8]:

	id	number
count	9651.000000	9651.000000
mean	16611.000000	43.695161
std	2786.148058	47.622874
min	11786.000000	1.000000
25%	14198.500000	14.000000
50%	16611.000000	27.000000
75%	19023.500000	46.000000
max	21436.000000	229.000000

In [9]:

```
rest.head(10)
```

Out[9]:

	id	object_name	address	chain	object_type	number
0	11786	HABITAT COFFEE SHOP	3708 N EAGLE ROCK BLVD	False	Cafe	26
1	11787	REILLY'S	100 WORLD WAY # 120	False	Restaurant	9
2	11788	STREET CHURROS	6801 HOLLYWOOD BLVD # 253	False	Fast Food	20
3	11789	TRINITI ECHO PARK	1814 W SUNSET BLVD	False	Restaurant	22
4	11790	POLLEN	2100 ECHO PARK AVE	False	Restaurant	20
5	11791	THE SPOT GRILL	10004 NATIONAL BLVD	False	Restaurant	14
6	11792	CPK	100 WORLD WAY # 126	False	Restaurant	100
7	11793	PHO LALA	3500 W 6TH ST STE 226	False	Restaurant	7
8	11794	ABC DONUTS	3027 N SAN FERNANDO RD UNIT 103	True	Fast Food	1
9	11795	UPSTAIRS	3707 N CAHUENGA BLVD	False	Restaurant	35

In [10]:

```
rest['object_type'].unique()
```

Out[10]:

```
array(['Cafe', 'Restaurant', 'Fast Food', 'Bakery', 'Bar', 'Pizza'],
      dtype=object)
```

In [11]:

```
rest = rest.astype({'chain': 'bool', 'object_type': 'category'})
```

Data looks clean. Did minor transformations:

- filled 3 NA values
- changed data types of some columns

Restaurants on the Map

Before we begin, let's take a bird's-eye view of the location of restaurants in LA on the map.

Geocoding the addresses:

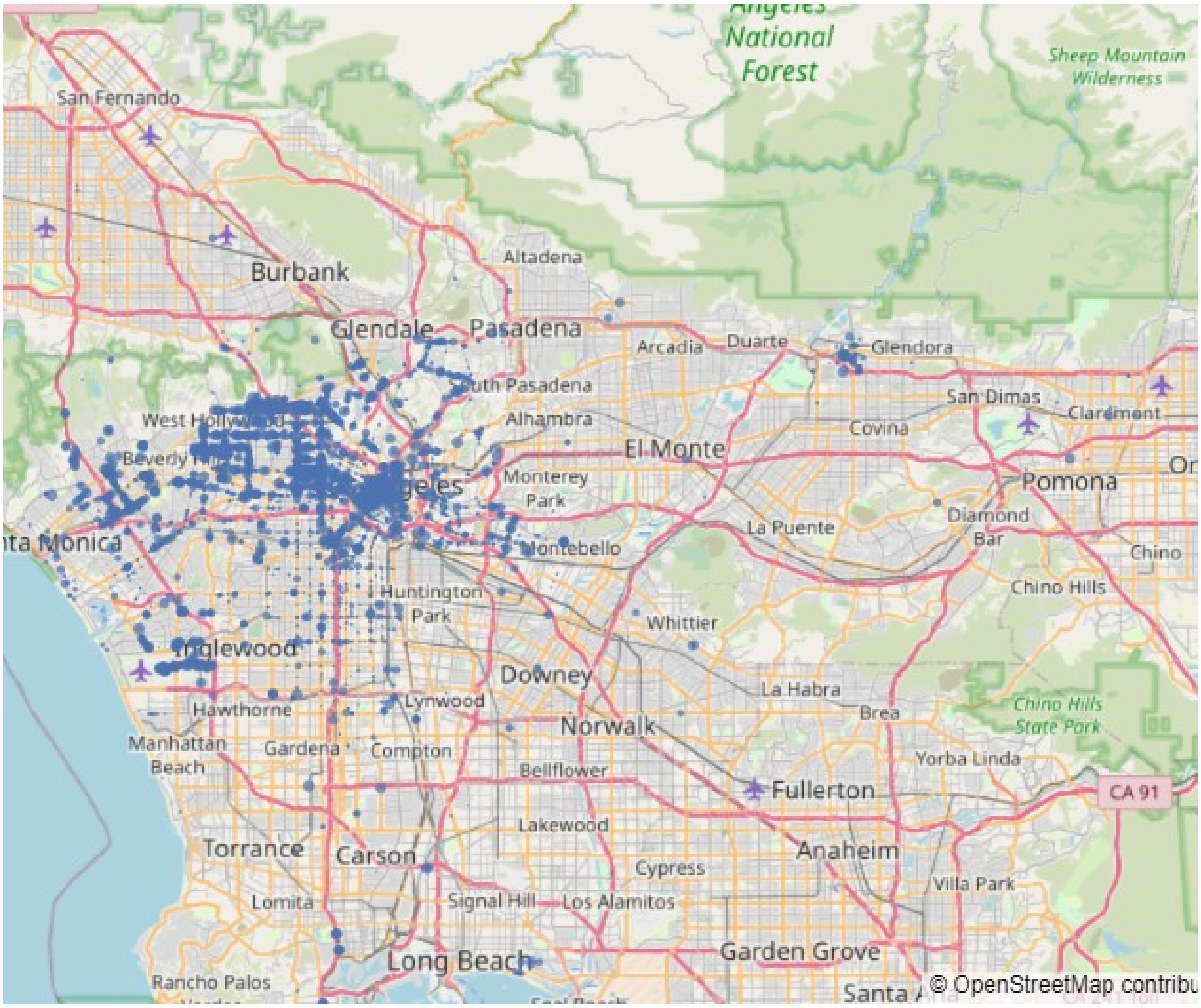
In [12]:
```
#####################
# I geocoded the restaurant addresses using this code. But since it took almost two
# I saved the result in a separate file.
#####################

### Original code
#
# from geopy.geocoders import Nominatim
# import time
#
# geolocator = Nominatim(user_agent="my-app")
# addresses = rest[['id','address']]
# def geocode_with_retry(address):
#     max_retries = 10
#     for i in range(1, max_retries):
#         try:
#             location = geolocator.geocode(address)
#             if location is not None:
#                 return location.latitude, location.longitude
#             else:
#                 return None, None
#         except:
#             print(f'Geocoder unavailable, retrying in {i} seconds...')
#             time.sleep(i)
#     print(f'Geocoding failed after {max_retries} retries')
#     return None, None
#
# addresses[['latitude', 'longitude']] = pd.DataFrame((addresses['address']).apply(
# addresses.to_csv('addresses.csv', index=False)

### Replacement code
addresses = pd.read_csv('addresses.csv')

#####################

print(f"Geocoded successfully: {(~addresses['longitude'].isna()).sum()} "
      f"out of {len(addresses)} addresses "
      f"({(~addresses['longitude'].isna()).sum()/len(addresses):.0%})")
```

```
Geocoded successfully: 7826 out of 9651 addresses (81%)
```

In [13]:
```
# Merging coordinates with the main table.
rest = rest.merge(addresses[['id','latitude','longitude']], on='id')
```

In [14]:
```
fig = px.scatter_mapbox(
    rest[~rest['latitude'].isna()],
    lat='latitude',
    lon='longitude',
    hover_name='object_name',
#     color='object_type',
    size='number',
```

```
    size_max=5,
    zoom=9,
    # height=1000
)
fig.update_layout(mapbox_style="open-street-map")
fig.update_layout(margin={"r":0,"t":0,"l":0,"b":0})
fig.show()
```



Data Analysis

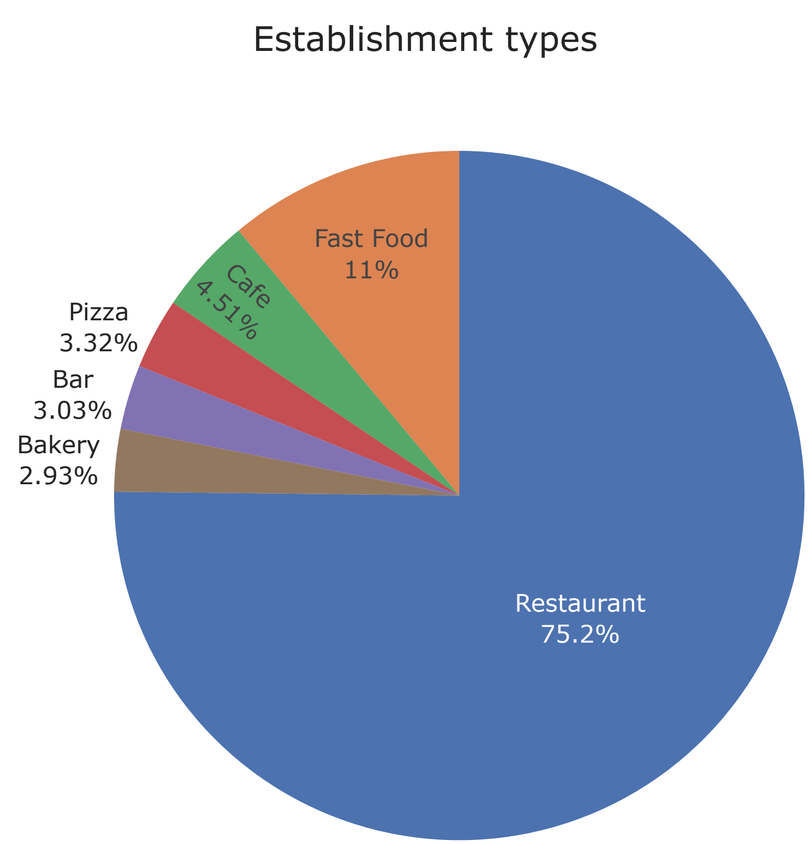
Investigate proportions of the various types of establishments

In [15]:
```
len(rest)
```

Out[15]:
```
9651
```

In [16]:
```
rest_type = rest.groupby('object_type')['id'].count().reset_index().sort_values(by=
rest_type.columns = ['est_type','count']
```

```
#display(rest_type)
fig = px.pie(
    rest_type,
    values='count',
    names='est_type',
    title='Establishment types',
)
fig.update_traces(
    textposition='auto',
    textinfo='percent+label',
    showlegend=False)
fig.show()
```



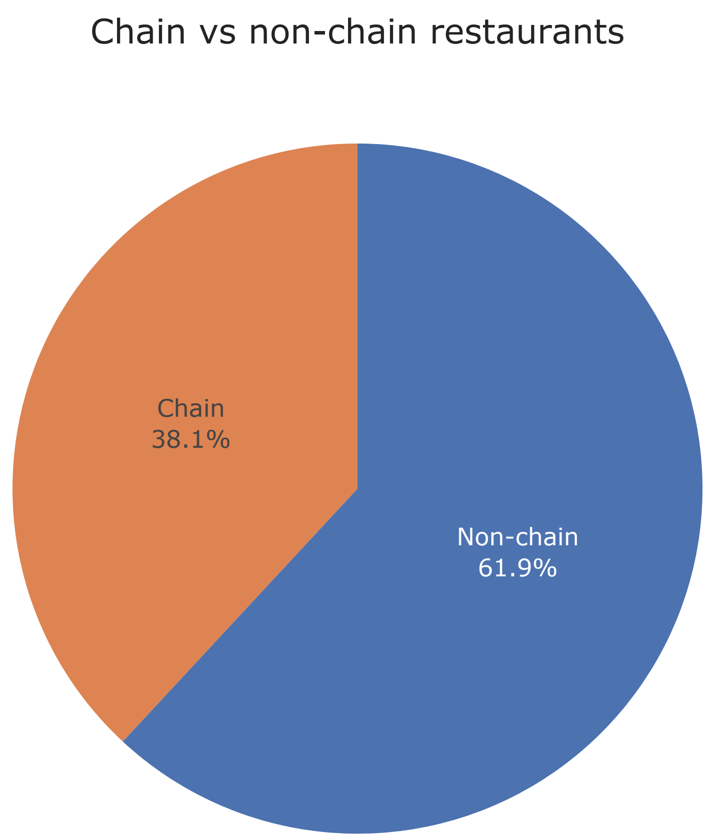
Observations:

- Restaurants make up over 75% of the market.
- Fast food establishments represent a respectable 11%, which is noteworthy given that all other types of establishments are under 5%.
- Cafes make up 4.5% of the market, while bakeries account for 2.9%.

Investigate proportions of chain and nonchain

establishments

In [17]:
```
fig = px.pie(
    rest.groupby('chain')['object_name'].count().reset_index().replace({True: 'Chai
    values='object_name',
    names='chain',
    title='Chain vs non-chain restaurants')
fig.update_traces(textposition='auto', textinfo='percent+label', showlegend=False)
fig.show()
```

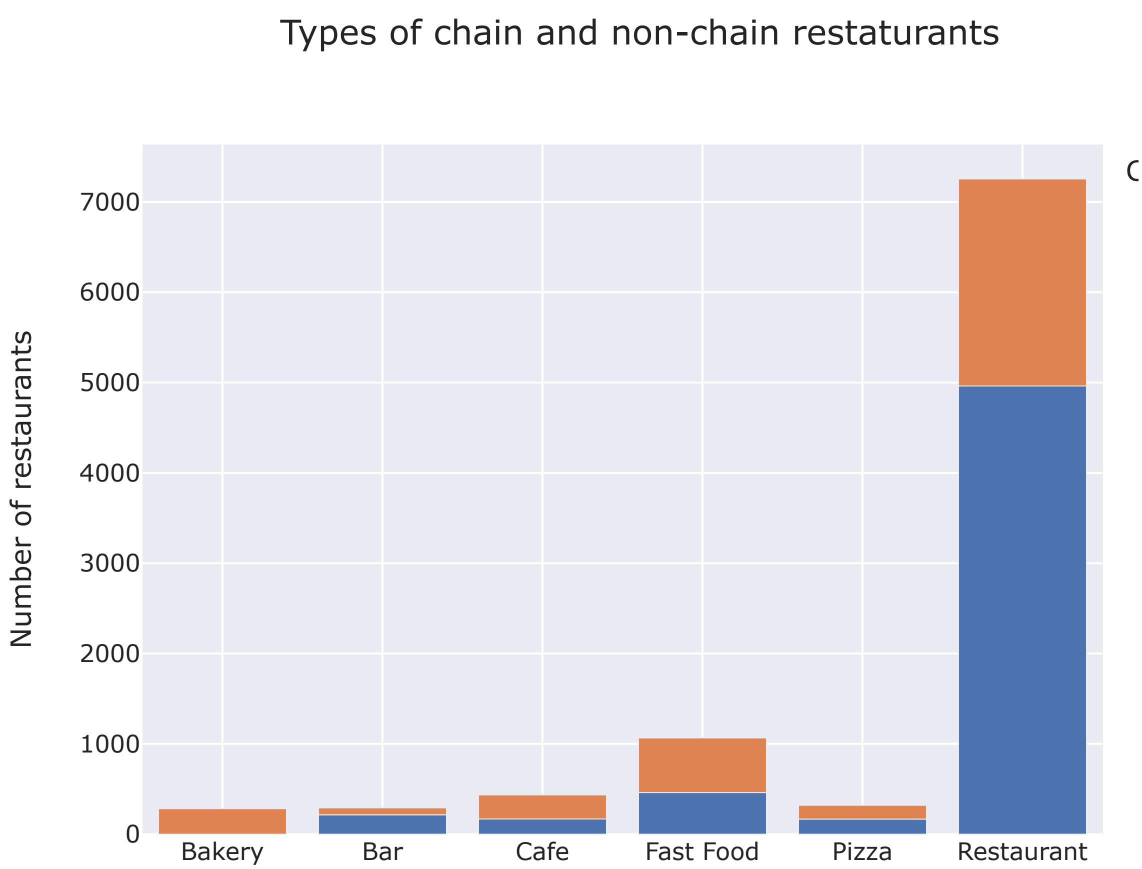


We can also note that almost 62% of the establishments are nonchain establishments. On the other hand, 38% of the establishments belong to chains.

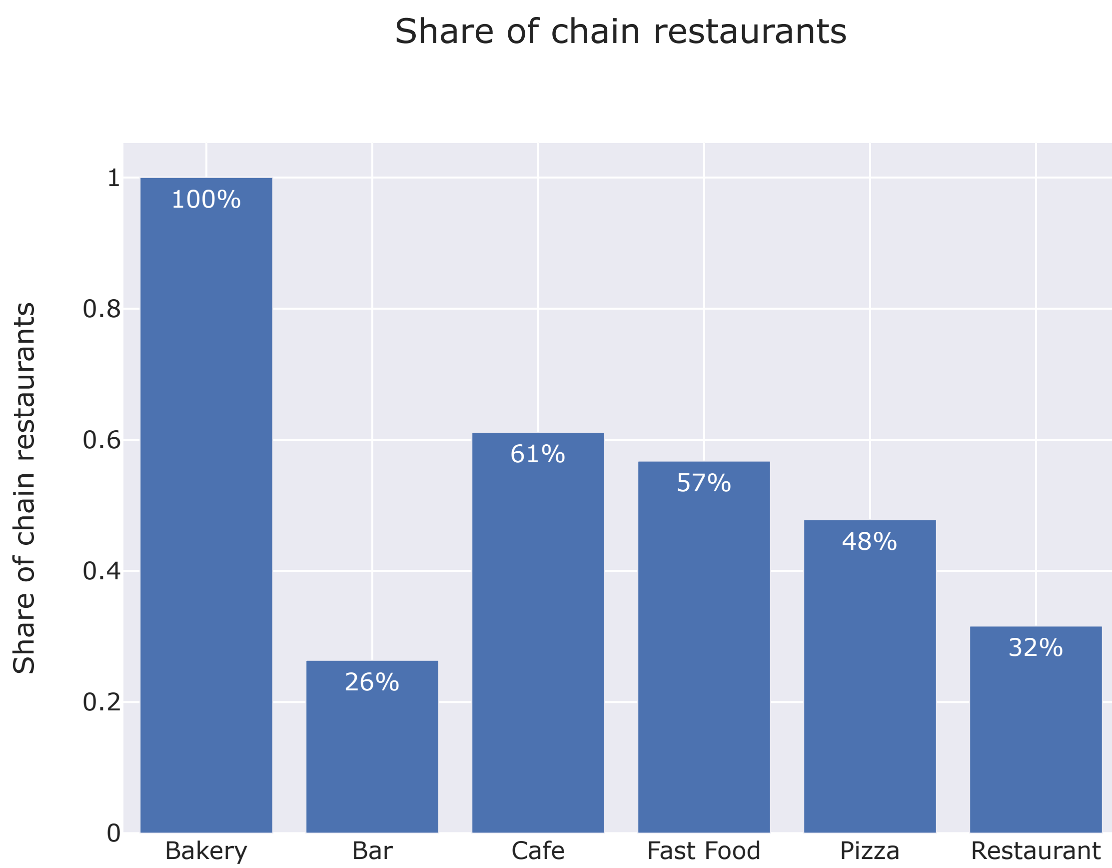
Which type of establishment is typically a chain?

In [18]:
```
rest_types = rest.pivot_table(
                index='object_type',
                columns='chain',
                values='id',
                aggfunc='count')
#display(rest_types)
```

```
fig = px.bar(
    rest_types,
    title='Types of chain and non-chain restaturants',
    labels={'value':'Number of restaurants', 'object_type':'Establishment type','ch
#    text_auto=True
)
fig.show()
```



In [19]:
```
fig = px.bar(
    rest_types[True] / ( rest_types[True]+rest_types[False]),
    title='Share of chain restaurants',
    text_auto='.0%',
    labels={'value':'Share of chain restaurants', 'object_type':'Establishment type
)
fig.update_layout(showlegend=False)
fig.show()
```



Observations:

- All bakeries belong to chains
- Bars are the least likely to belong to chains (only 26%)

What characterizes chains: many establishments with a small number of seats or a few establishments with a lot of seats?

In [20]:

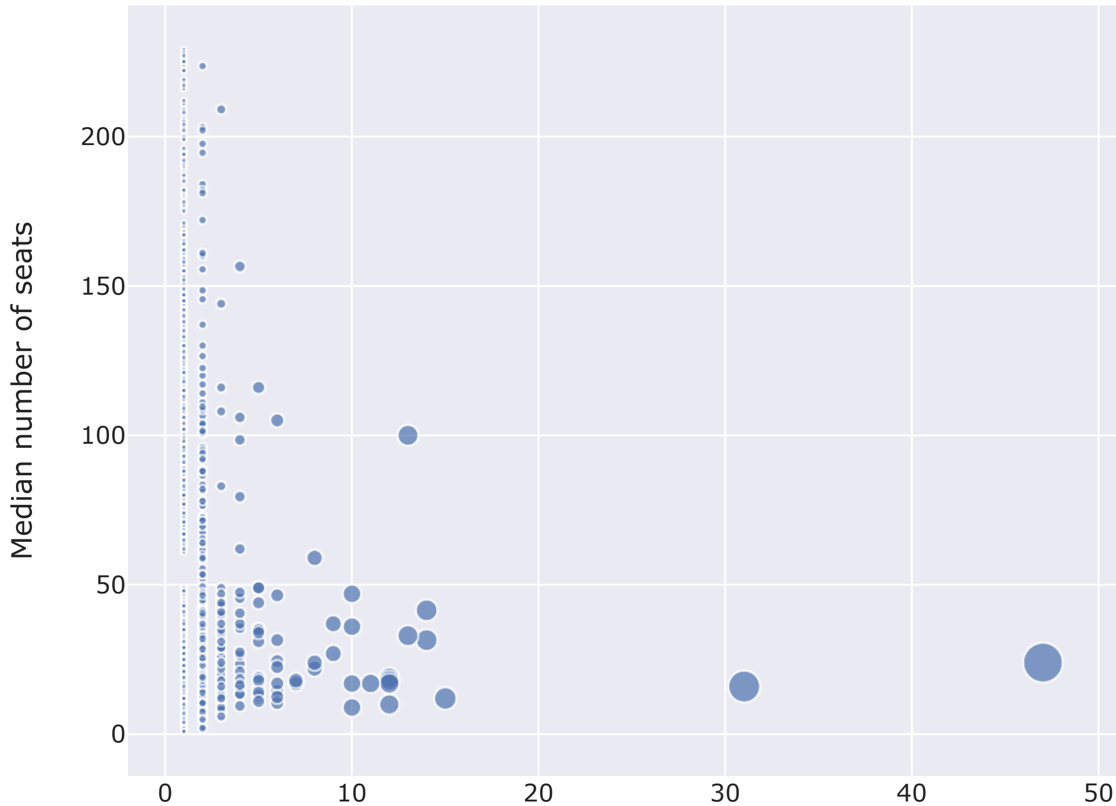
```
chains = rest[rest['chain'] == True
    ].groupby('object_name')['id', 'number'
    ].agg({'id': 'count', 'number': 'median'}
    ).rename(columns={'id': 'count', 'number': 'median_seats'}
        ).sort_values(by='count', ascending=False)

chains.head(10)
```

Out[20]:

object_name	count	median_seats
THE COFFEE BEAN & TEA LEAF	47	24.0
SUBWAY	31	16.0
DOMINO'S PIZZA	15	12.0
WABA GRILL	14	41.5
KENTUCKY FRIED CHICKEN	14	31.5
MCDONALD'S	13	100.0
TRIMANA	13	33.0
STARBUCKS	12	19.0
PAPA JOHN'S PIZZA	12	10.0
YOGURTLAND	12	18.0

In [21]:

```
fig = px.scatter(
        chains,
        x='count',
        y='median_seats',
        labels={'count':'Number of restaurants', 'median_seats':'Median number of s
        size='count',
)
fig.show()
```

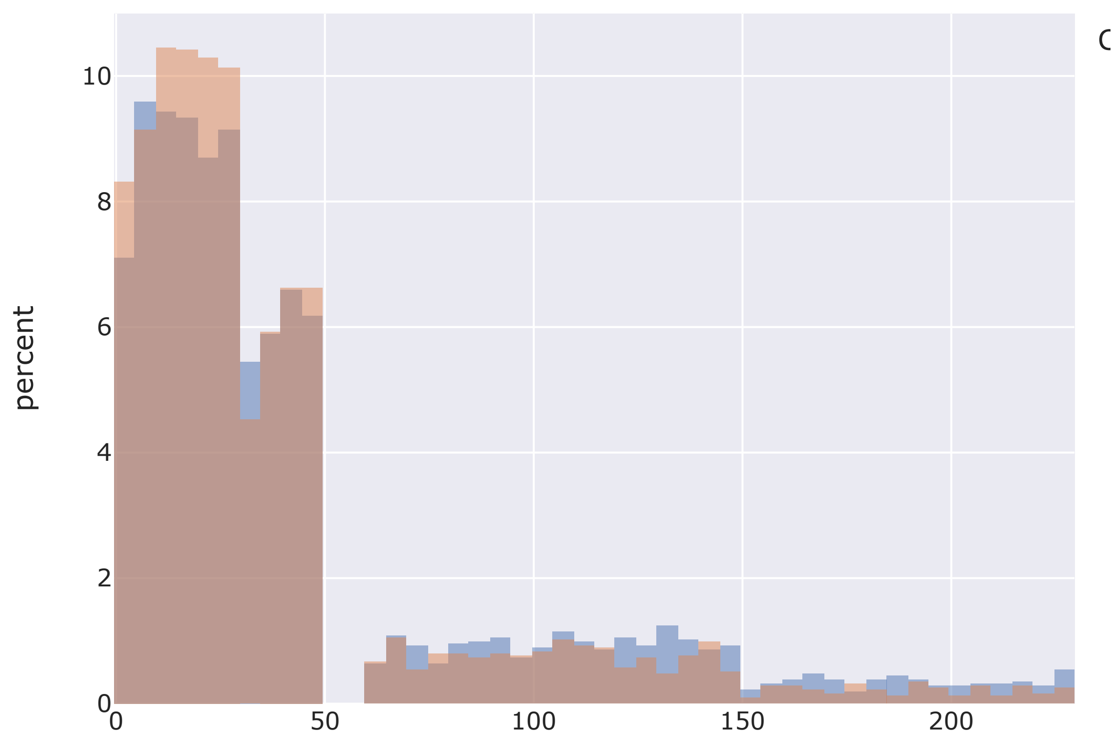


Obeservation: the bigger the chain, the less median number of seats it has.

Determine the average number of seats for each type of restaurant. On average, which type of restaurant has the greatest number of seats? Plot graphs

In [22]:
```
fig = px.histogram(
    rest,
    x='number',
    color = 'chain',
    barmode='overlay',
    title="Number of seats distribution",
    histnorm='percent',
    labels={'number':'Number of seats', 'chain':'Chain'}
    )
fig.show()
```

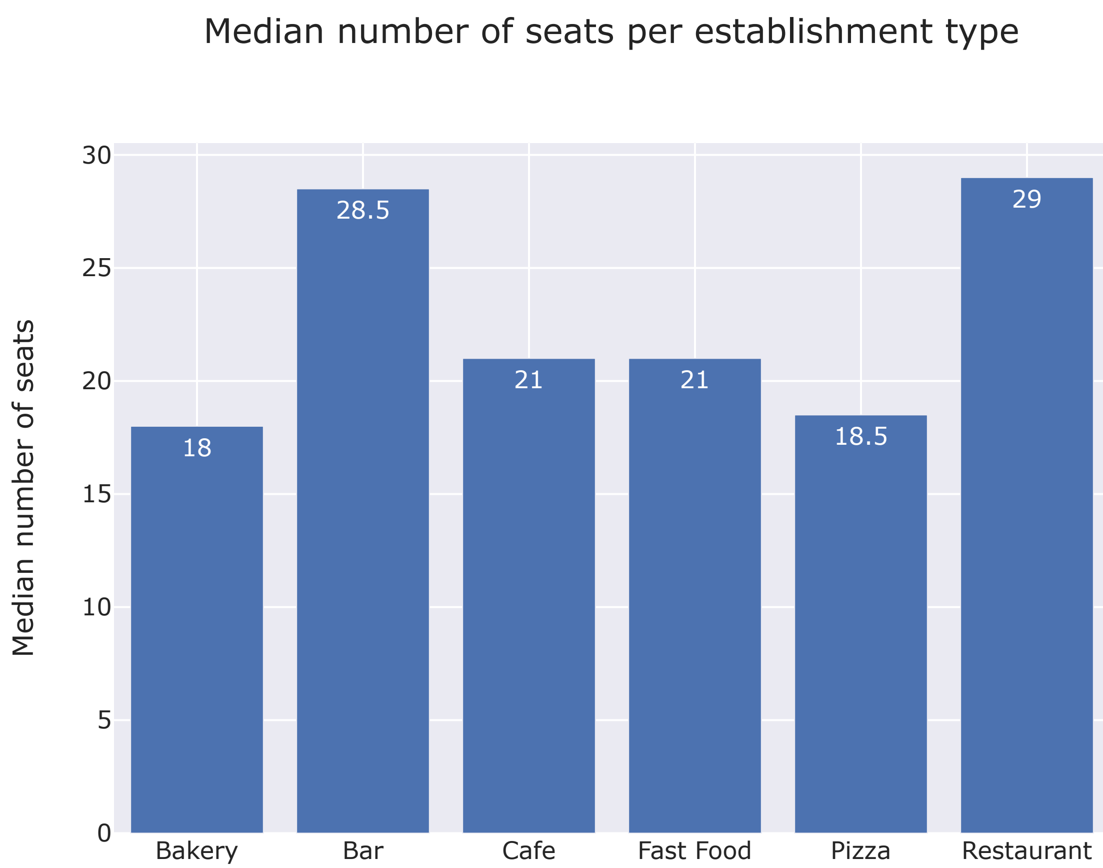
Number of seats distribution



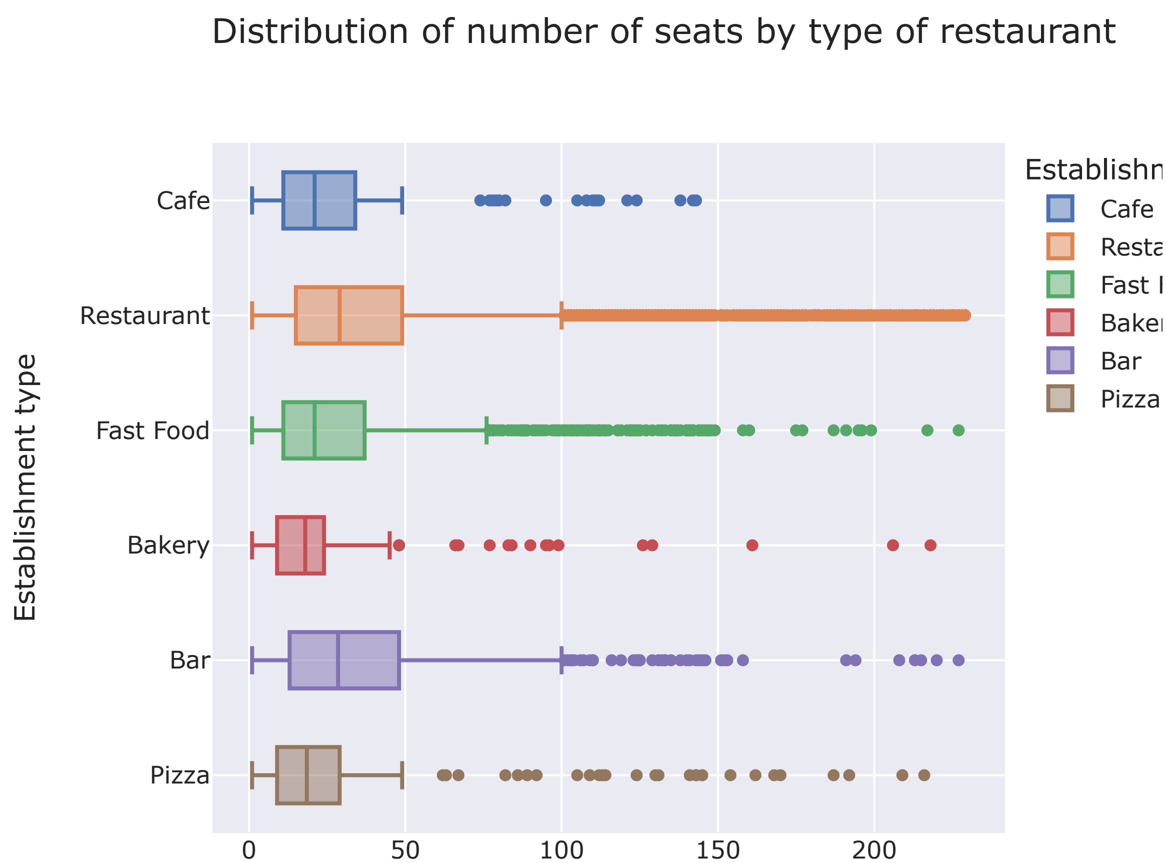
Observations:

- Chain and non-chain restaurants have similar distribution the number of seats
- Most establishments have fewer than 50 seats
- For some reason there are no establishments in the dataset that have between 50 and 60 seats.

In [23]:
```
fig = px.bar(
    rest.pivot_table(
                index='object_type',
                values='number',
                aggfunc='median',
        ),
    title='Median number of seats per establishment type',
        text_auto=True,
        labels={'value':'Median number of seats', 'object_type':'Establishment type
)
fig.update_traces(showlegend=False)
fig.show()
```



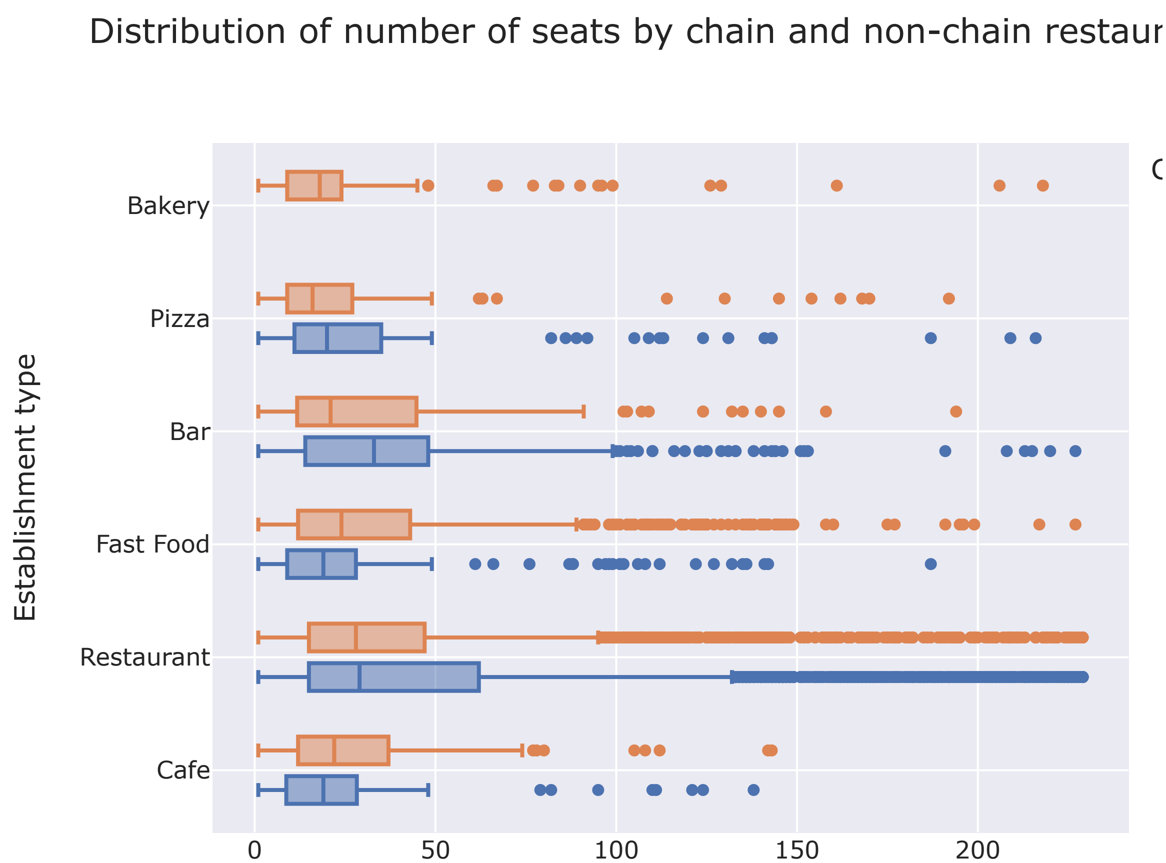

```
In [24]: fig = px.box(
        rest,
        x='number',
        y='object_type',
        color='object_type',
        title='Distribution of number of seats by type of restaurant',
        labels={'number':'Number of seats', 'object_type':'Establishment type'}
)
fig.show()
```



Observations:

- Restaurants and bars have the highest mean number of seats: 48 and 45
- Bakeries have the lowest mean number of seats - 21. Probably because many people use it as takeaways.

In [25]:
```
fig = px.box(
        rest,
        x='number',
        y='object_type',
        color='chain',
        title='Distribution of number of seats by chain and non-chain restaurants',
        labels={'number':'Number of seats', 'object_type':'Establishment type', 'ch
)
fig.show()
```



Chain establishments in the fast food and cafe categories typically have a greater number of seats than non-chain establishments, while in all other categories, they tend to have a smaller number of seats.

Put the data on street names from the address column in a separate column

In [26]:

```
def extract_street(address):
    parsed_address = usaddress.parse(address)
    street = ''
    for component in parsed_address:
        if component[1] == 'StreetName':
            street += component[0] + ' '
    return street.strip()

rest['street'] = rest['address'].apply(extract_street)
rest.head()
```

Out[26]:

	id	object_name	address	chain	object_type	number	latitude	longitude	
0	11786	HABITAT COFFEE SHOP	3708 N EAGLE ROCK BLVD	False	Cafe	26	NaN	NaN	EAGLI
1	11787	REILLY'S	100 WORLD WAY # 120	False	Restaurant	9	33.945488	-118.399701	V
2	11788	STREET CHURROS	6801 HOLLYWOOD BLVD # 253	False	Fast Food	20	34.102690	-118.340469	HOLLY
3	11789	TRINITI ECHO PARK	1814 W SUNSET BLVD	False	Restaurant	22	34.068635	-118.469970	S
4	11790	POLLEN	2100 ECHO PARK AVE	False	Restaurant	20	34.089478	-118.249866	ECH

Plot a graph of the top ten streets by number of restaurants

In [27]:

```
rest_by_street = rest.groupby('street')['id'].count().sort_values(ascending=False)
rest_by_street.head(10)
```

Out[27]:

```
street
SUNSET          404
WILSHIRE        398
PICO            370
WESTERN         369
FIGUEROA        334
OLYMPIC         309
VERMONT         288
SANTA MONICA    264
3RD             263
HOLLYWOOD       253
Name: id, dtype: int64
```

In [28]:

```
len(rest_by_street)
```

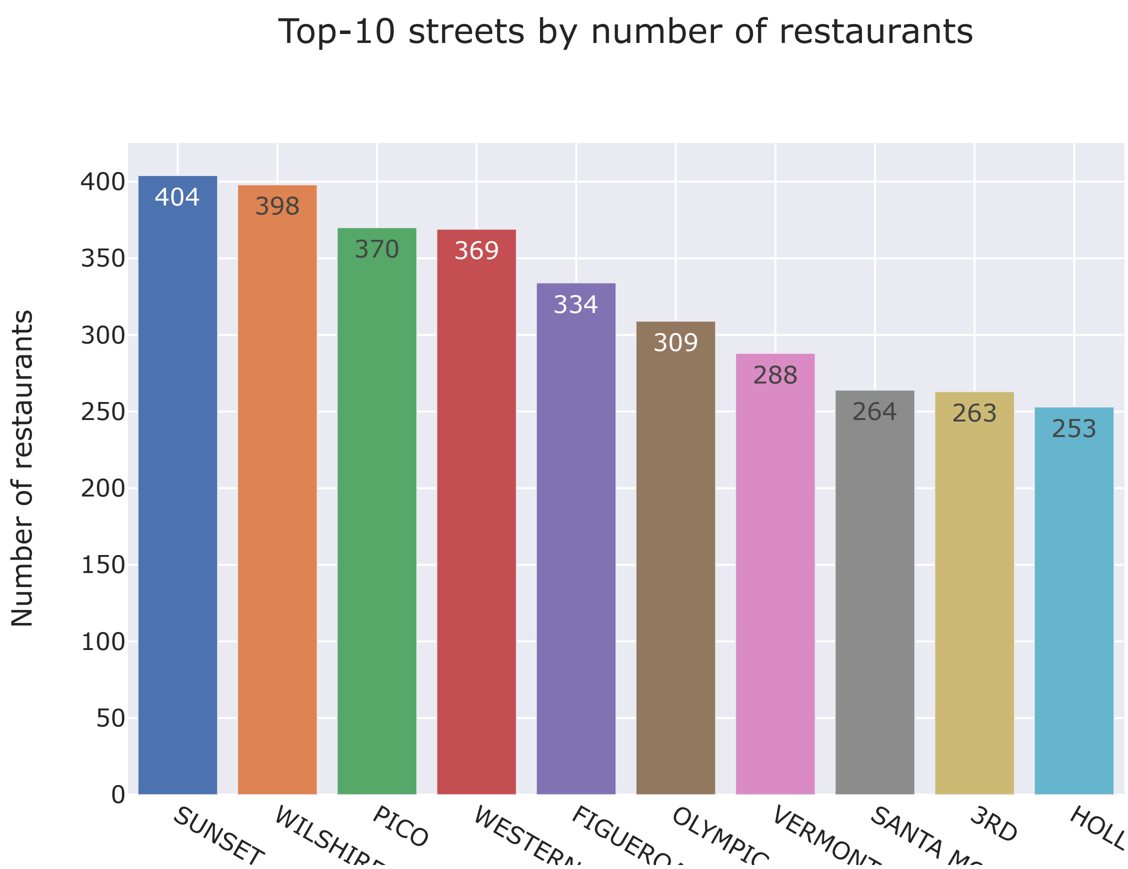
Out[28]:

```
491
```

There are 491 streets with restaurants in LA

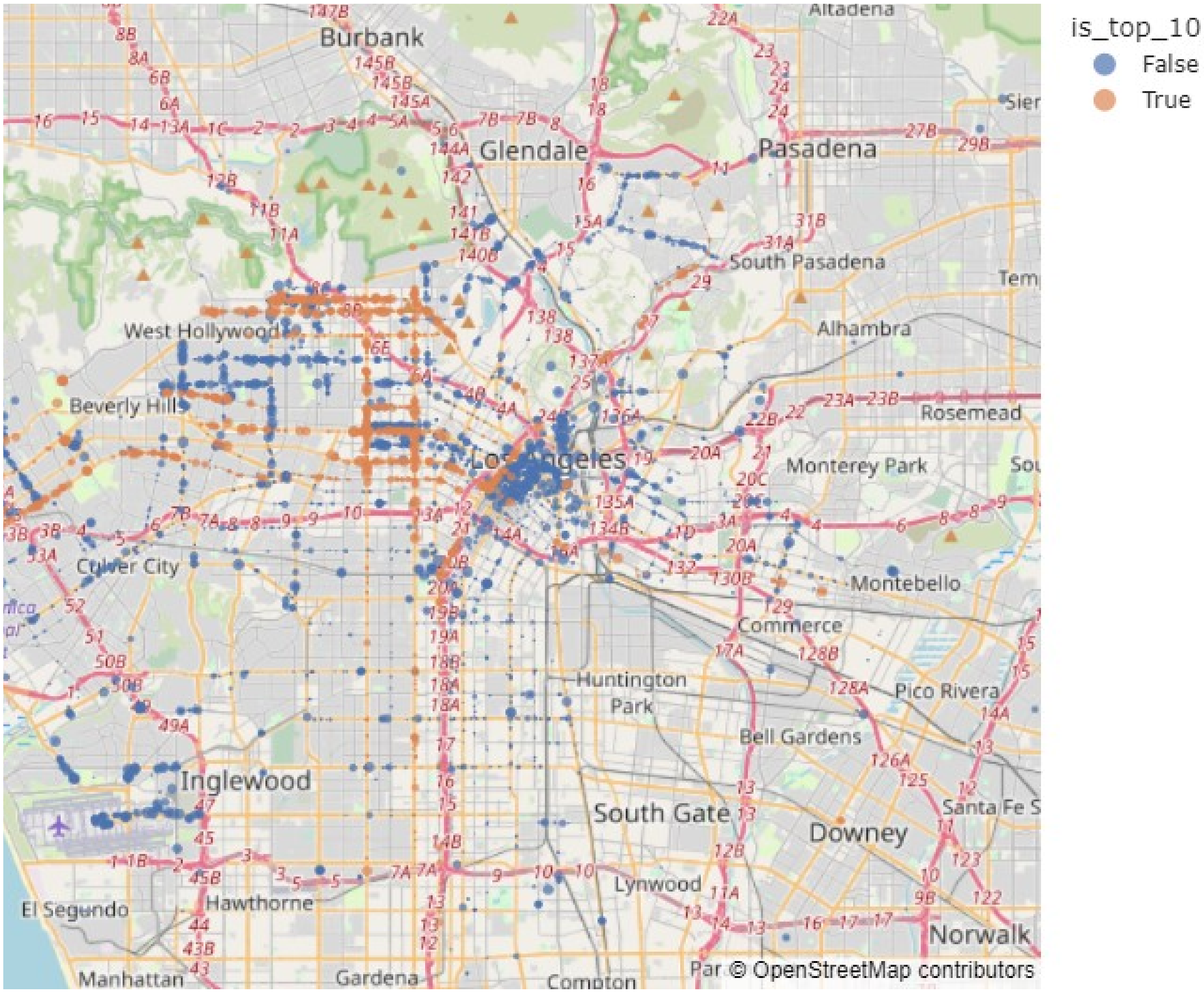
In [29]:

```
fig = px.bar(
        rest_by_street.head(10),
        title='Top-10 streets by number of restaurants',
        text='value',
        color = rest_by_street.head(10).index,
        labels={'street':'Street', 'value':'Number of restaurants'}
)
fig.update_layout(showlegend=False)
fig.show()
```

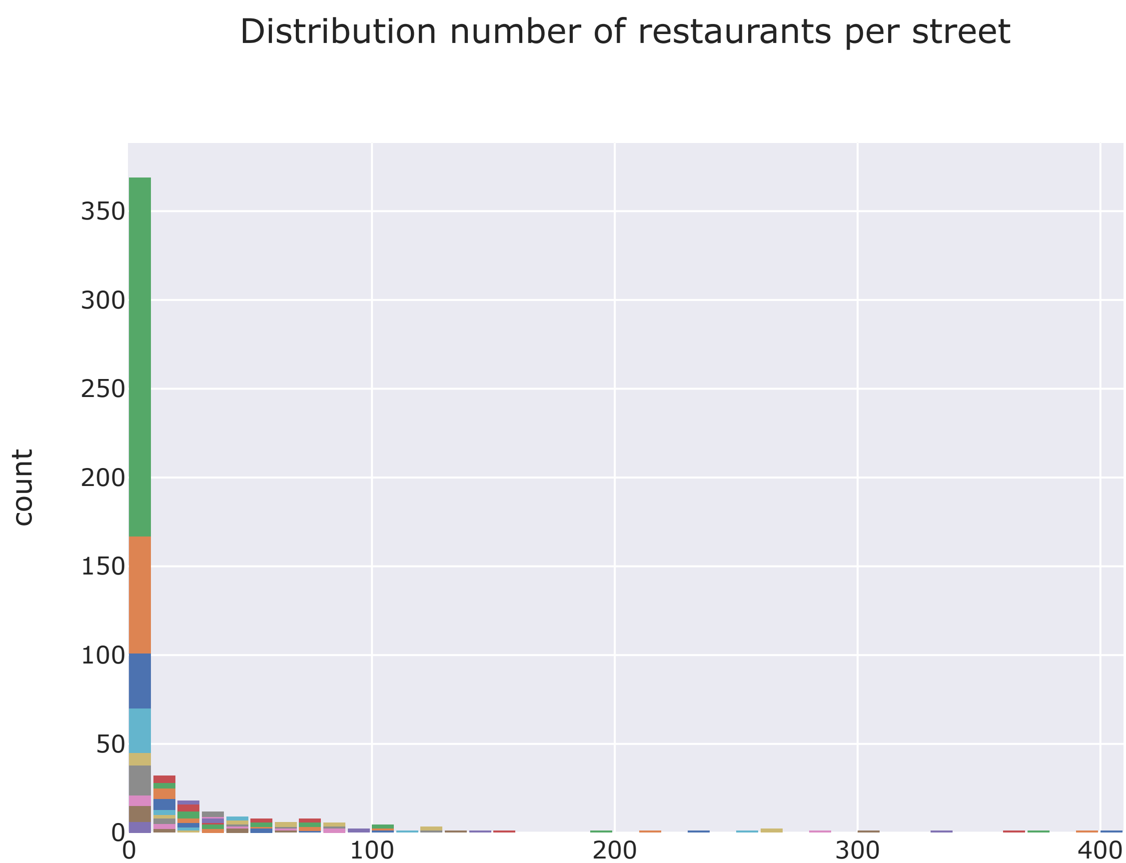


Out of the 491 streets in the dataset, the top 10 streets account for 34% of all restaurants, with each of these streets having an average of 325 (!) restaurants. The street with the highest number of restaurants is Sunset Street, with a total of 404 restaurants.

In [30]:
```python
rest['is_top_10'] = rest['street'].isin(rest_by_street.head(10).index)
fig = px.scatter_mapbox(
    rest[~rest['latitude'].isna()],
    lat='latitude',
    lon='longitude',
    hover_name='object_name',
    color='is_top_10',
    size='number',
    size_max=5,
    zoom=10,
    # height=1000
)
fig.update_layout(mapbox_style="open-street-map")
fig.update_layout(margin={"r":0,"t":0,"l":0,"b":0})
fig.show()
```

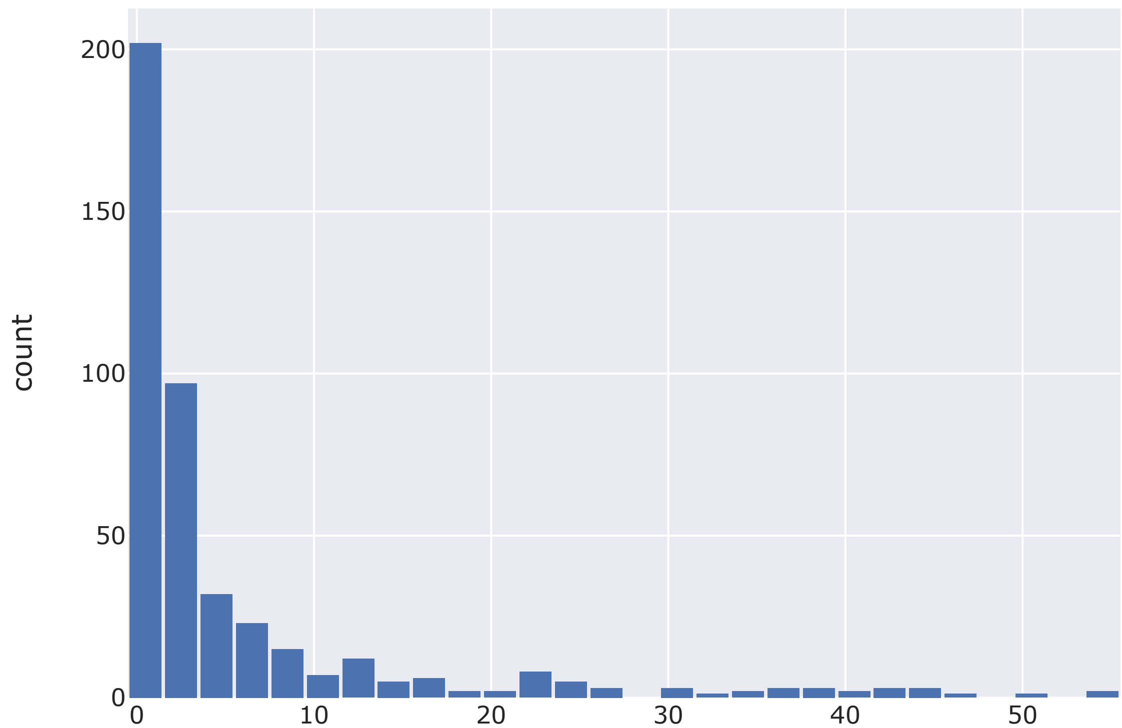


In [31]:
```
fig = px.histogram(
        rest_by_street,
        title = 'Distribution number of restaurants per street',
        color='value',
    labels={'value':'Restaurants per street', 'count':'Number of streets'}
)
fig.update_layout(bargap=0.1,showlegend=False)
fig.show()
```



In [32]:
```
quantile = 90
fig = px.histogram(
        rest_by_street[rest_by_street.values <= np.percentile(rest_by_street.values
        title = f"Distribution of number of restaurants per street within {quantile
    labels={'value':'Restaurants per street', 'count':'Number of streets'}
)
fig.update_layout(bargap=0.1)
fig.show()
```

Distribution of number of restaurants per street within 90% qu



70% of streets have less than 10 resturants

Find the number of streets that only have one restaurant

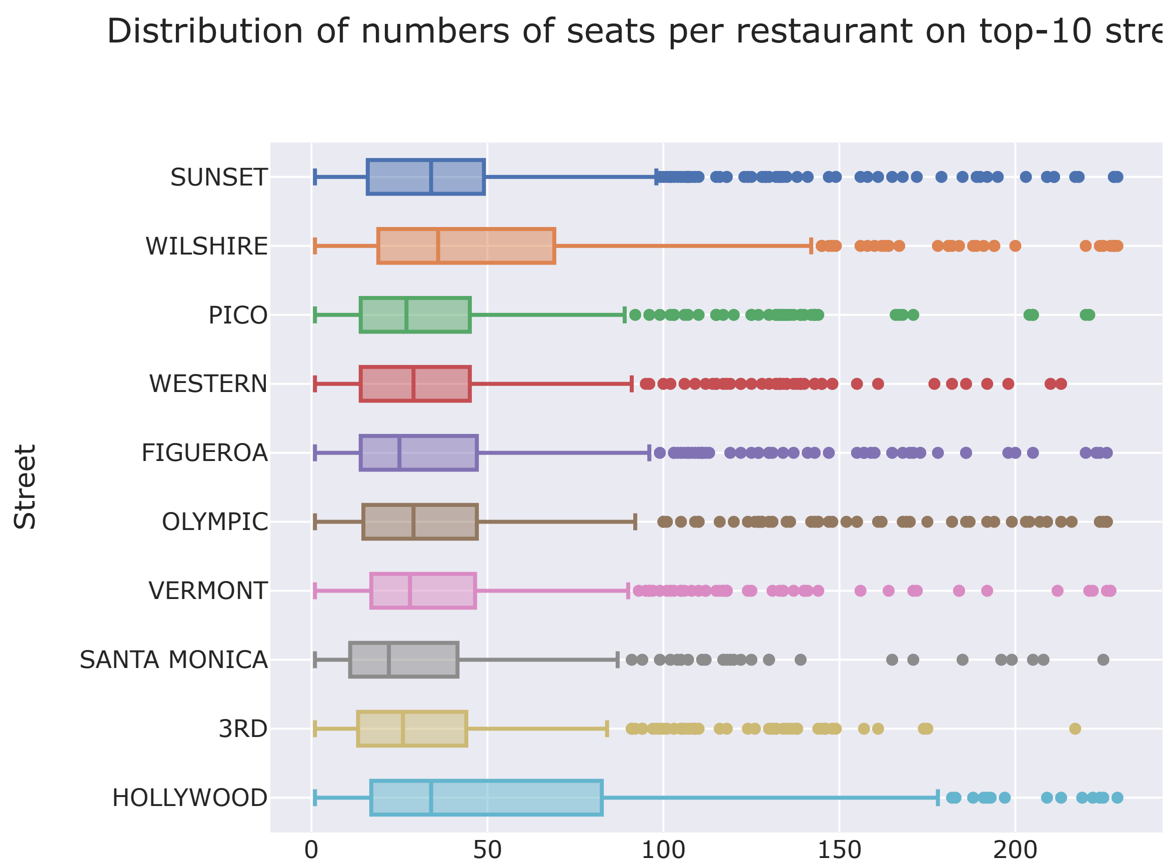
In [33]:
```
print(f"Number of streets that only have one restaurant: {rest_by_street[rest_by_st
```

```
Number of streets that only have one restaurant: 202
```

For streets with a lot of restaurants, look at the distribution of the number of seats. What trends can you see?

In [34]:
```
fig = px.box(
        rest[rest['street'].isin(rest_by_street.head(10).index)],
        x='number',
        y='street',
        color='street',
        title='Distribution of numbers of seats per restaurant on top-10 streets',
        category_orders={'street':rest_by_street.head(10).index},
```

```
        labels={'street':'Street', 'number':'Number of seats'}
)
fig.update_layout(showlegend=False)
fig.show()
```



Wilshire street has the largest median number of seats.

Conclusion and recommendations

Findings

- Most establishments in Los Angeles are restaurants, making up 75% of the market
- In Los Angeles, 62% of establishments are independently owned, while the remaining 38% are chain establishments.
- The highest share of chain establishments is in Bakeries (100%). The lowest share is among Bars (26%).
- Chain and non-chain restaurants have similar distribution the number of seats. Most establishments have fewer than 50 seats

- For some reason there are no establishments in the dataset that have between 50 and 60 seats.
- Restaurants and bars have the highest median number of seats at 29 and 28.5, respectively. Bakeries have the lowest mean number of seats, which is 18, likely because many customers prefer to order takeaways.
- Chain establishments in the fast food and cafe categories tend to have more seats than non-chain establishments, while in all other categories, they tend to have fewer seats.
- The top 10 streets out of 491 streets in the dataset account for 34% of all restaurants, with each street averaging 325 restaurants. Meanwhile, 70% of streets have less than 10 restaurants. Sunset Boulevard has the highest number of restaurants, with a total of 404.

Recommendations

We recommend considering the possibility of launching a bar based on the following factors:

- Bars are generally preferred by customers who value small, genuine settings, leading to a minimal presence of chains in this market.
- In Los Angeles, bars have the lowest representation among all categories (excluding bakeries, which are not relevant since they are completely dominated by chains).