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My primary interest for this EDA is:

- Feature Relationships: Analyzing the distribution of continuous magnitude (mag) across categorical factors like network source (net) and the engineered ordinal categories (mag_ordinal, depth_ordinal) to see if the different locations of network would have impact on the data.

- Quantitative Relationships: Quantify the relationships between numerical features the topic is interested in, such as `magnitude`, `depth`, `latitidue`, `longitdue`, `network sorce`, `magnitude ordinal` and `depth ordinal`.

- Spatial Distribution: Mapping earthquake epicenters, particularly identifying regions prone to high-magnitude or deep events.

In [1]:
```
import pandas as pd
import altair as alt
import numpy as np
import altair as alt
alt.renderers.enable("mimetype")
alt.data_transformers.enable("vegafusion")
```

Out[1]:
```
DataTransformerRegistry.enable('vegafusion')
```

In [2]:
```
df = pd.read_csv("../../data/processed/ordinal_data.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	time	latitude	longitude	depth	mag	magType	nst	gap	dmin
0	2025-10-23T22:11:40.587Z	32.274000	-101.931000	4.2122	1.40	ml	40.0	40.0	0.000000
1	2025-10-23T22:09:24.260Z	38.806835	-122.751999	-0.6400	1.27	md	13.0	110.0	0.023310
2	2025-10-23T22:08:01.540Z	38.807835	-122.751167	0.1900	1.24	md	12.0	112.0	0.023690
3	2025-10-23T22:07:48.630Z	38.834332	-122.796333	2.2500	0.23	md	10.0	76.0	0.006201
4	2025-10-23T22:01:31.590Z	38.808998	-122.811668	3.6600	0.74	md	10.0	83.0	0.012830

5 rows × 25 columns

In [4]:
```python
df.columns
```

Out[4]:
```
Index(['time', 'latitude', 'longitude', 'depth', 'mag', 'magType', 'nst',
       'gap', 'dmin', 'rms', 'net', 'id', 'updated', 'place', 'type',
       'horizontalError', 'depthError', 'magError', 'magNst', 'status',
       'locationSource', 'magSource', 'mag_ordinal', 'depth_ordinal',
       'gap_level'],
      dtype='object')
```

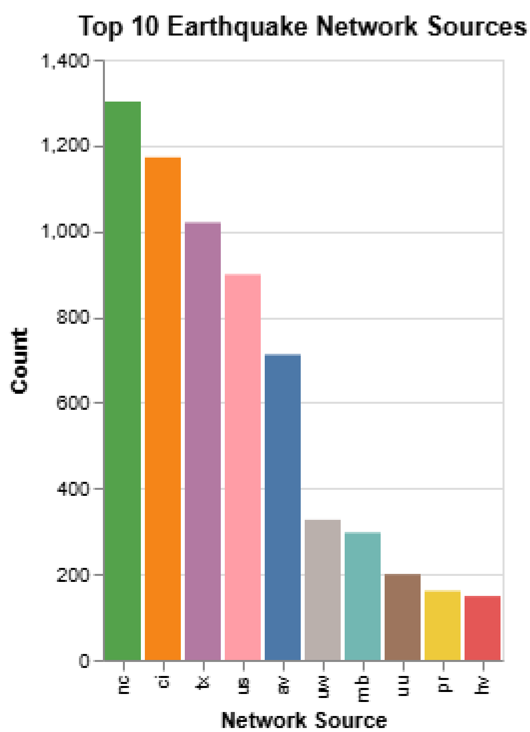
In [5]:
```python
depth_order = ['Negative (<0 km)', 'Shallow (0-70 km)', 'Intermediate (70-300 km)',
gap_order = ['poor', 'moderate-low', 'moderate-high', 'high']
mag_order = ['Minor (<4.0)', 'Light (4.0-4.9)', 'Moderate (5.0-5.9)', 'Strong (6.0-
core_cols = [
    'mag', 'depth', 'gap', 'latitude', 'longitude'
]
```

Different Network Potential Geographic Impact On Data

We will be studying the most popular network sources and identify patterns that could be potentially caused by the location difference.

In [6]:
```python
net_counts = df['net'].value_counts().nlargest(10).index.tolist()
net_bar = alt.Chart(df[df['net'].isin(net_counts)]).mark_bar().encode(
    alt.X("net:N", title="Network Source", sort="-y"),
    alt.Y("count()", title="Count"),
    color=alt.Color("net:N", legend=None)
).properties(title="Top 10 Earthquake Network Sources")
net_bar
```

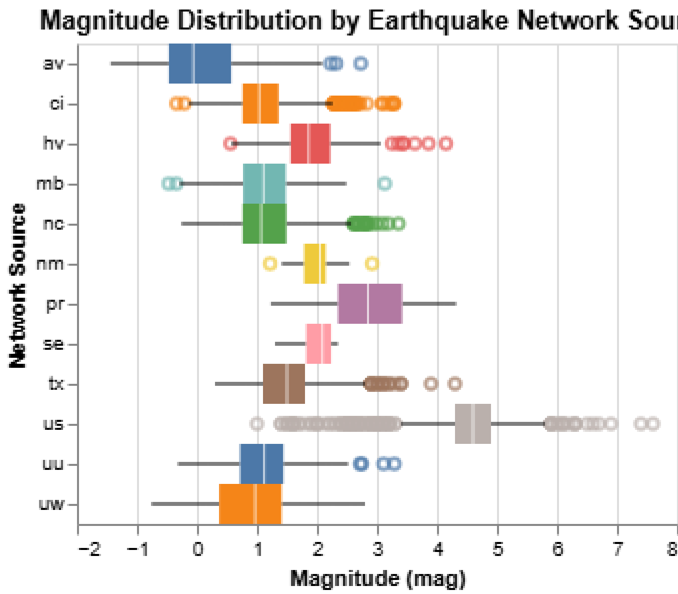
Out[6]:



In [7]:
```python
mag_net_boxplot = alt.Chart(df).mark_boxplot(extent=1.5, size=20).encode(
    alt.Y('net:N', title='Network Source', sort=alt.EncodingSortField(field="mag",
```

```
    alt.X('mag:Q', title='Magnitude (mag)'),
    alt.Color('net:N', legend=None),
    tooltip=['net', 'median(mag)', 'min(mag)', 'max(mag)']
).properties(
    title='Magnitude Distribution by Earthquake Network Source'
).interactive()
mag_net_boxplot
```

Out[7]:

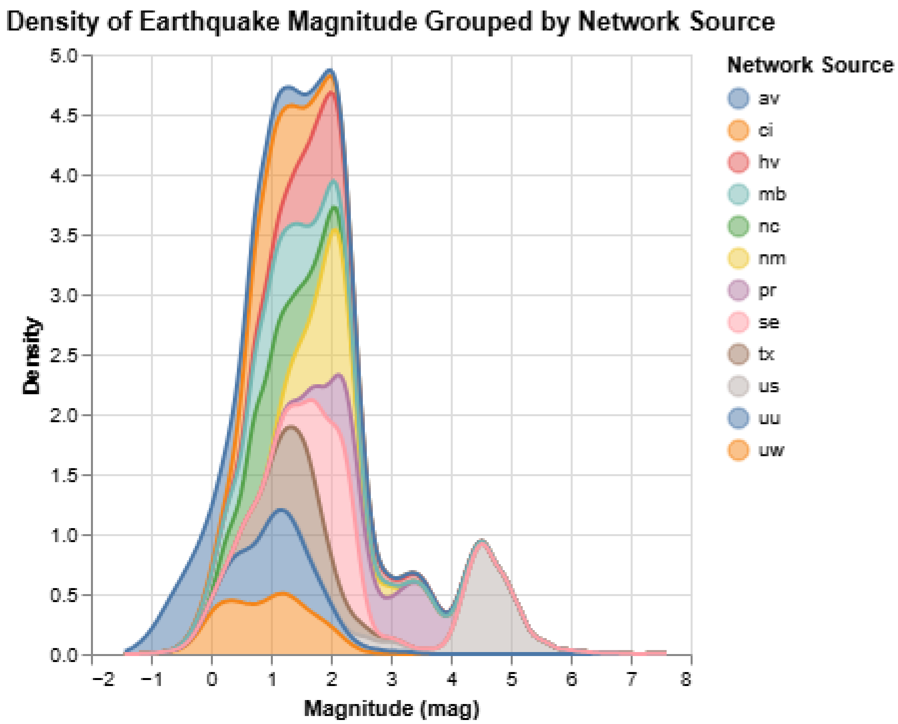


Despite the different locations, each network have pretty similar and consistent results, with US being the exception. Our interpretation is US is likely recording the most earthquakes around the world and that could contribute to more outliers.

In [8]:

```
net_density_chart = alt.Chart(df).transform_density(
    'mag',
    groupby=['net'],
    as_=['mag', 'density']
).mark_area(
    opacity=0.5,
    line={'color':'darkgrey'}
).encode(
    x=alt.X('mag:Q', title='Magnitude (mag)'),
    y=alt.Y('density:Q', title='Density'),  # Force quantitative
    color=alt.Color('net:N', title='Network Source'),
    tooltip=[alt.Tooltip('net:N'), alt.Tooltip('mag:Q'), alt.Tooltip('density:Q')]
).properties(
    title='Density of Earthquake Magnitude Grouped by Network Source'
)

net_density_chart
```

Out[8]:



The graph clearly separates the goals of the seismic networks:

- High-Density Regional Networks: ('ci', 'hv', 'nc', etc.) prioritize detection completeness and high resolution for small-to-micro earthquakes to study local fault mechanics.
- Broad-Scope Global Network: ('us') prioritizes breadth of coverage and the reliable recording of moderate-to-large events that pose a hazard.

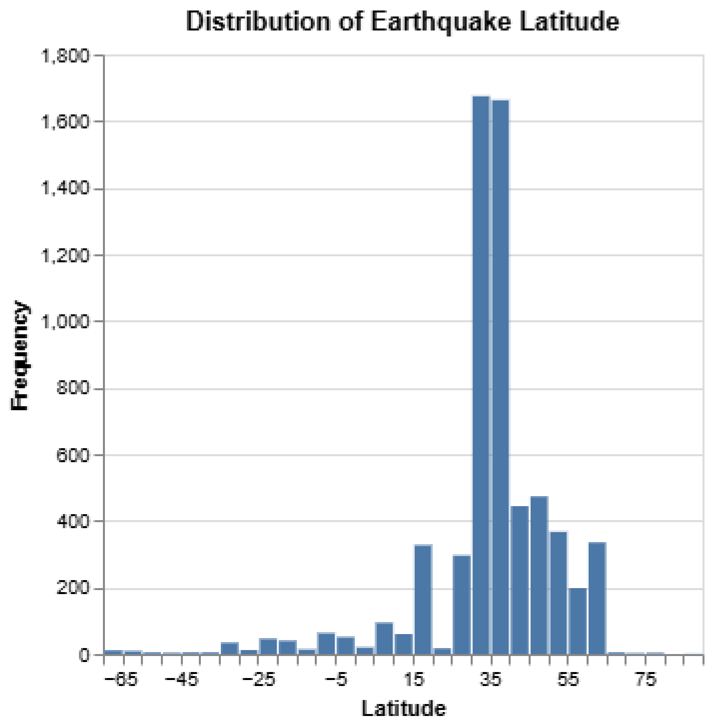
Geolocation of Earthquakes

The following graphs are a collection basic bar charts of the frequency of earthquakes in relation to the respective attributes of interest:

In [9]:

```
lat_hist = alt.Chart(df).mark_bar().encode(
    alt.X("latitude:Q", bin=alt.Bin(maxbins=50), title="Latitude"),
    alt.Y("count()", title="Frequency")
).properties(title="Distribution of Earthquake Latitude")
lat_hist
```

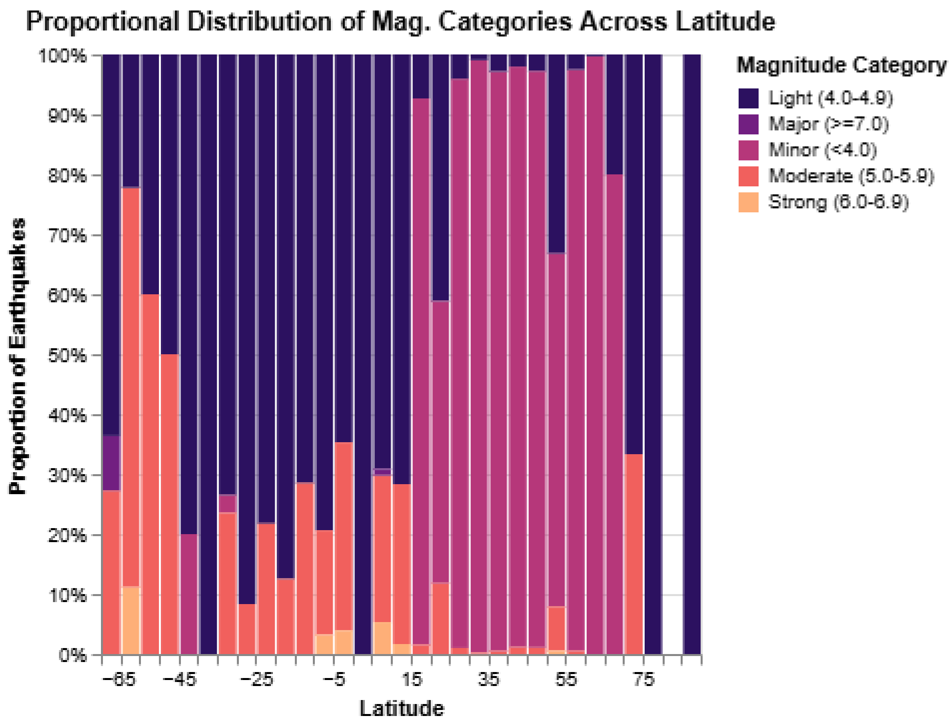
Out[9]:



In [10]:

```
lat_proportional_hist = alt.Chart(df).mark_bar(
    strokeWidth=0,
    stroke=None
).encode(
    alt.X("latitude:Q", bin=alt.Bin(maxbins=30), title="Latitude"),
    alt.Y("count()", stack="normalize", title="Proportion of Earthquakes"),
    alt.Color("mag_ordinal:O", title="Magnitude Category",
              scale=alt.Scale(scheme='magma')),
    tooltip=[
        alt.Tooltip('latitude:Q', bin=True, title='Latitude Bin'),
        alt.Tooltip('mag_ordinal:O', title='Magnitude Category'),
        alt.Tooltip('count():Q', title='Count'),
    ]
).properties(
    title="Proportional Distribution of Mag. Categories Across Latitude"
)

lat_proportional_hist
```

Out[10]:

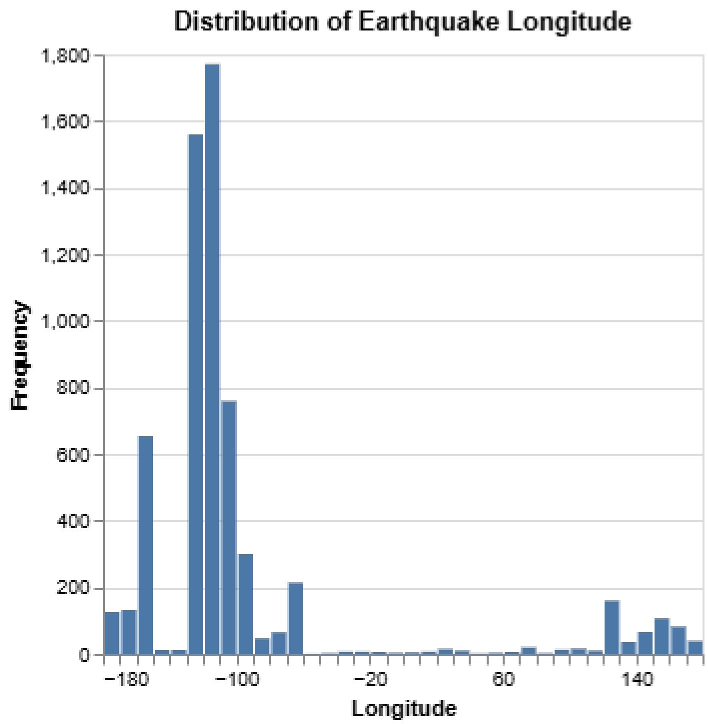


The chart visually demonstrates that while small earthquakes occur everywhere, the most severe seismic hazard, represented by the proportion of Strong and Major quakes, is highly concentrated geographically, particularly at the extremes of the sampled latitude range (high northern and high southern latitudes), corresponding to major plate boundaries like the Circum-Pacific Belt.

In [11]:

```
lon_hist = alt.Chart(df).mark_bar().encode(
    alt.X("longitude:Q", bin=alt.Bin(maxbins=50), title="Longitude"),
    alt.Y("count()", title="Frequency")
).properties(title="Distribution of Earthquake Longitude")
lon_hist
```

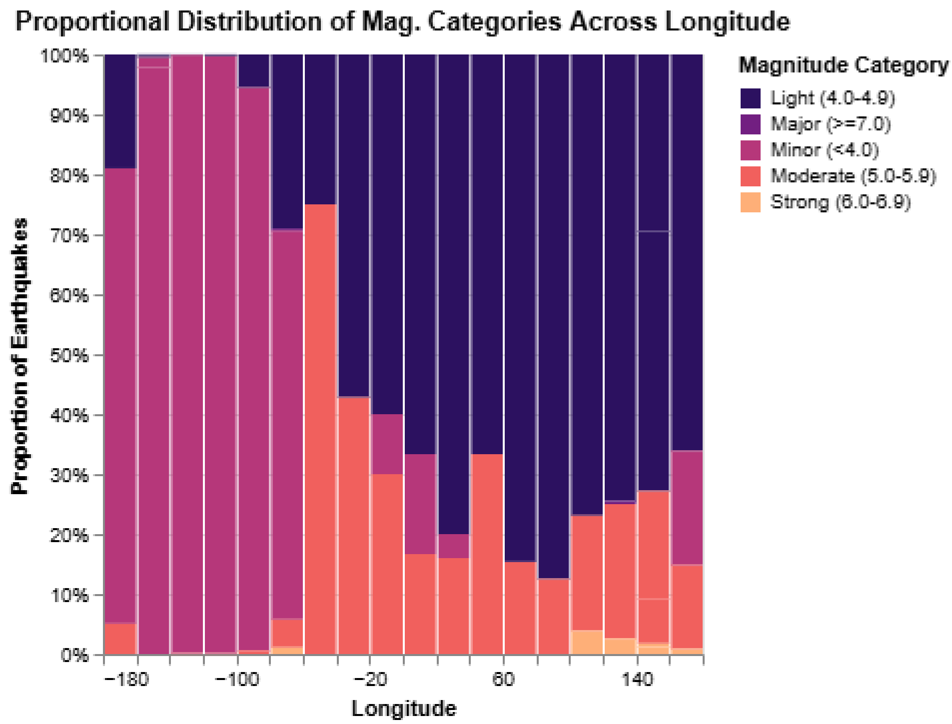
Out[11]:



In [12]:

```
lon_proportional_hist = alt.Chart(df).mark_bar(
    strokeWidth=0,
    stroke=None
).encode(
    alt.X("longitude:Q", bin=alt.Bin(maxbins=30), title="Longitude"),
    alt.Y("count()", stack="normalize", title="Proportion of Earthquakes"),
    alt.Color("mag_ordinal:O", title="Magnitude Category",
              scale=alt.Scale(scheme='magma')),
    tooltip=[
        alt.Tooltip('longitude:Q', bin=True, title='Longitude Bin'),
        alt.Tooltip('mag_ordinal:O', title='Magnitude Category'),
        alt.Tooltip('count():Q', title='Count'),
    ]
).properties(
    title="Proportional Distribution of Mag. Categories Across Longitude"
)

lon_proportional_hist
```

Out[12]:

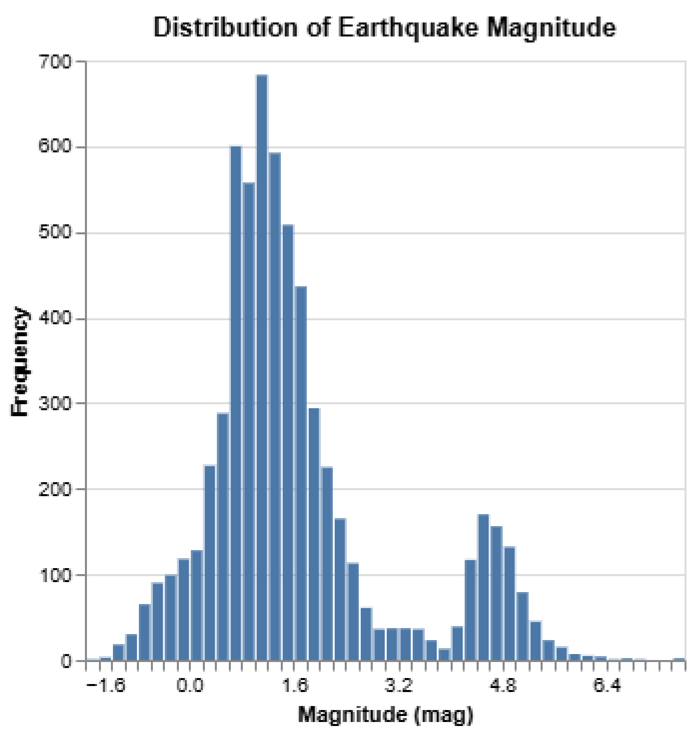


The chart graphically demonstrates that the seismic hazard (the relative proportion of larger, potentially damaging quakes) is concentrated along the Pacific margins (the Ring of Fire), particularly in the Western Hemisphere longitudes, while activity elsewhere is dominated by small, non-destructive events.

In [13]:

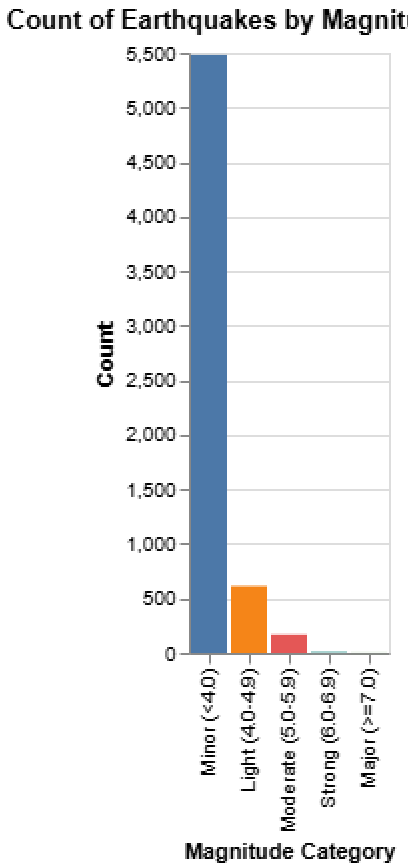
```
mag_hist = alt.Chart(df).mark_bar().encode(
    alt.X("mag:Q", bin=alt.Bin(maxbins=50), title="Magnitude (mag)"),
    alt.Y("count()", title="Frequency")
).properties(title="Distribution of Earthquake Magnitude")
mag_hist
```

Out[13]:



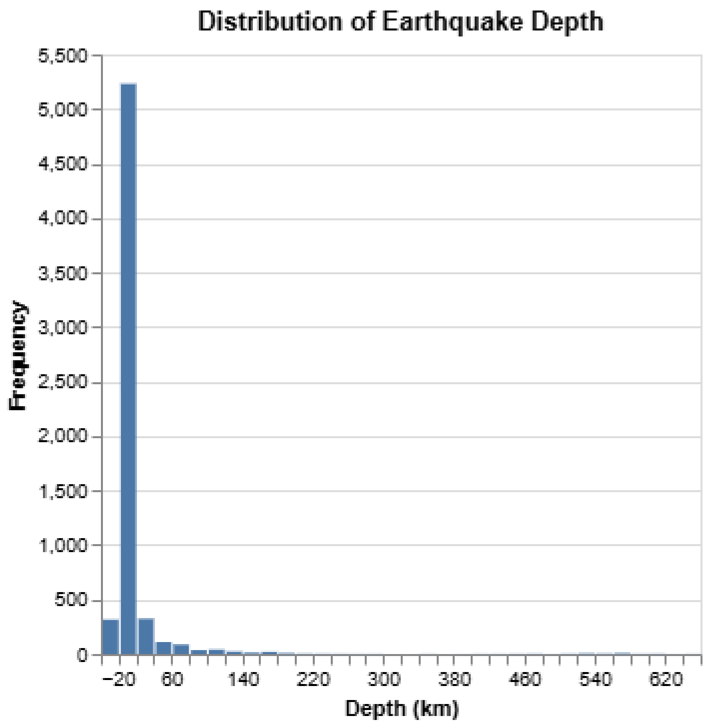
In [14]:
```
mag_ordinal_bar = alt.Chart(df).mark_bar().encode(
    alt.X("mag_ordinal:N", sort=mag_order, title="Magnitude Category"),
    alt.Y("count()", title="Count"),
    color=alt.Color("mag_ordinal:N", sort=mag_order, legend=None)
).properties(title="Count of Earthquakes by Magnitude Category")
mag_ordinal_bar
```

Out[14]:



In [15]:
```
depth_hist = alt.Chart(df).mark_bar().encode(
    alt.X("depth:Q", bin=alt.Bin(maxbins=50), title="Depth (km)"),
    alt.Y("count()", title="Frequency")
).properties(title="Distribution of Earthquake Depth")
depth_hist
```

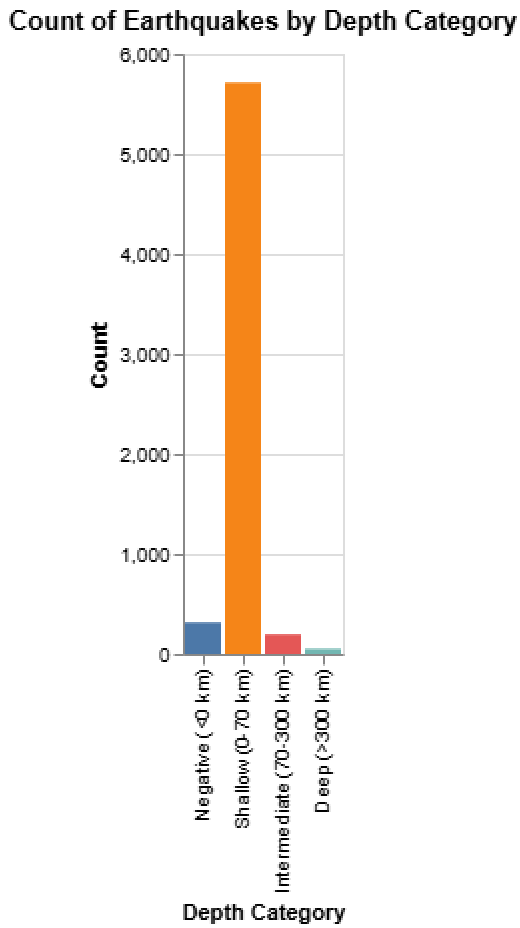
Out[15]:



In [16]:

```
depth_ordinal_bar = alt.Chart(df).mark_bar().encode(
    alt.X("depth_ordinal:N", sort=depth_order, title="Depth Category"),
    alt.Y("count()", title="Count"),
    color=alt.Color("depth_ordinal:N", sort=depth_order, legend=None)
).properties(title="Count of Earthquakes by Depth Category")
depth_ordinal_bar
```

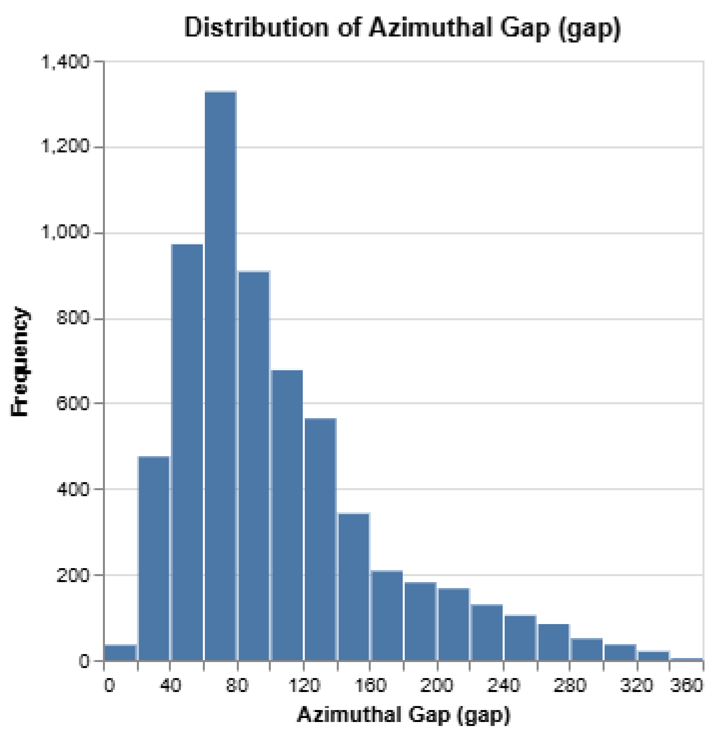
Out[16]:



In [17]:

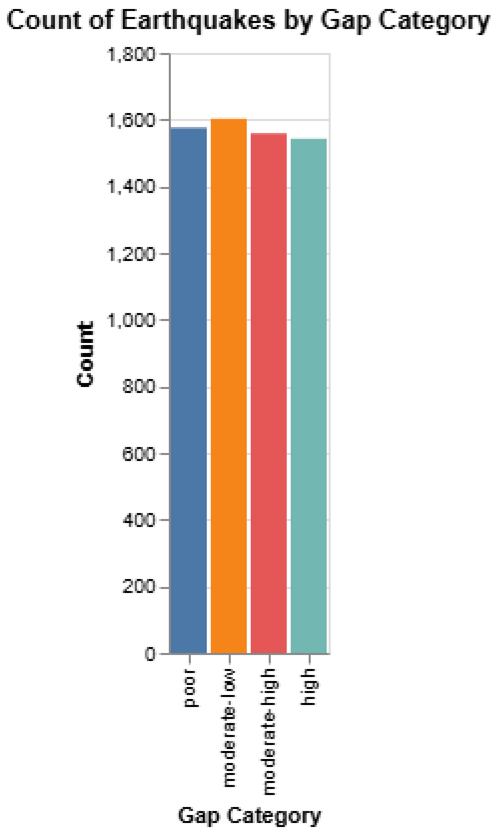
```
gap_hist = alt.Chart(df).mark_bar().encode(
    alt.X("gap:Q", bin=alt.Bin(maxbins=30), title="Azimuthal Gap (gap)"),
    alt.Y("count()", title="Frequency")
).properties(title="Distribution of Azimuthal Gap (gap)")
gap_hist
```

Out[17]:



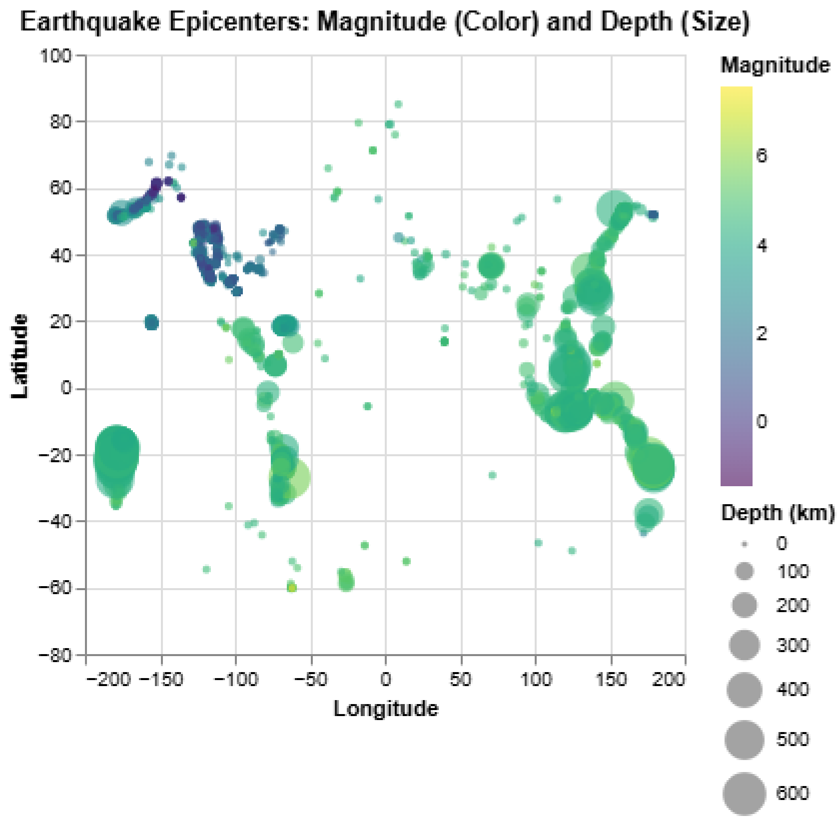
In [18]:
```python
depth_ordinal_bar = alt.Chart(df).mark_bar().encode(
    alt.X("gap_level:N", sort=gap_order, title="Gap Category"),
    alt.Y("count()", title="Count"),
    color=alt.Color("gap_level:N", sort=gap_order, legend=None)
).properties(title="Count of Earthquakes by Gap Category")
depth_ordinal_bar
```

Out[18]:



In [19]:
```python
spatial_map = alt.Chart(df).mark_circle(opacity=0.6).encode(
    alt.X('longitude:Q', title='Longitude'),
    alt.Y('latitude:Q', title='Latitude'),
    alt.Color('mag:Q', scale=alt.Scale(scheme='viridis', domain=[df['mag'].min(), d
    alt.Size('depth:Q', scale=alt.Scale(range=[5, 500], domain=[df['depth'].min(),
    tooltip=['place', 'mag', 'depth', 'mag_ordinal']
).properties(
    title='Earthquake Epicenters: Magnitude (Color) and Depth (Size)'
)
spatial_map
```

Out[19]:

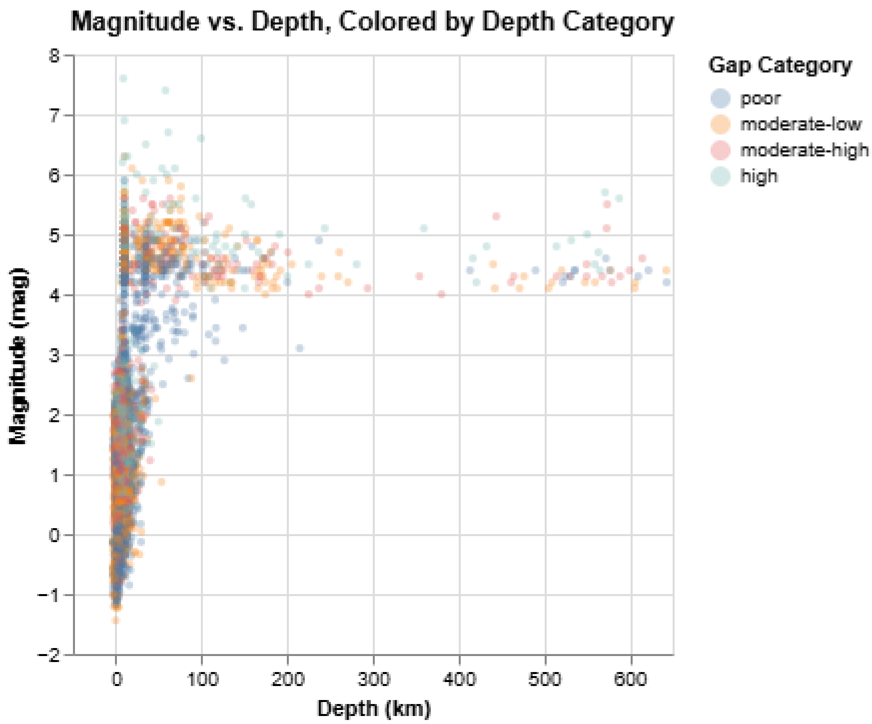


- Circum-Pacific Belt (Ring of Fire): The most striking feature is the dense clustering of earthquakes along the edges of the Pacific Ocean (roughly Longitude -180 to -70 and 100 to 180). This region is the famous "Ring of Fire," where the majority of the world's large, shallow, and deep earthquakes occur, primarily due to subduction zones.
- Absence in Continental Interiors: There are very few epicenters in the centers of major continental landmasses (e.g., central Africa, central North America, central South America, central Eurasia), confirming that most significant seismicity occurs at plate boundaries.
- Mid-Ocean Ridges: A scattered, linear pattern of small, shallow earthquakes is visible in the middle of the Atlantic Ocean and the southern Pacific (e.g., near Longitude -10, 0, and 100). These correspond to mid-ocean ridges (divergent boundaries), which typically produce many small, shallow quakes.

In [20]:

```
mag_depth_scatter = alt.Chart(df).mark_circle(size=15, opacity=0.3).encode(
    alt.X('depth:Q', title='Depth (km)'),
    alt.Y('mag:Q', title='Magnitude (mag)'),
    alt.Color('gap_level:N', sort=gap_order, title='Gap Category'),
    tooltip=['depth', 'mag', 'depth_ordinal']
).properties(
    title='Magnitude vs. Depth, Colored by Depth Category'
)
mag_depth_scatter
```

Out[20]:



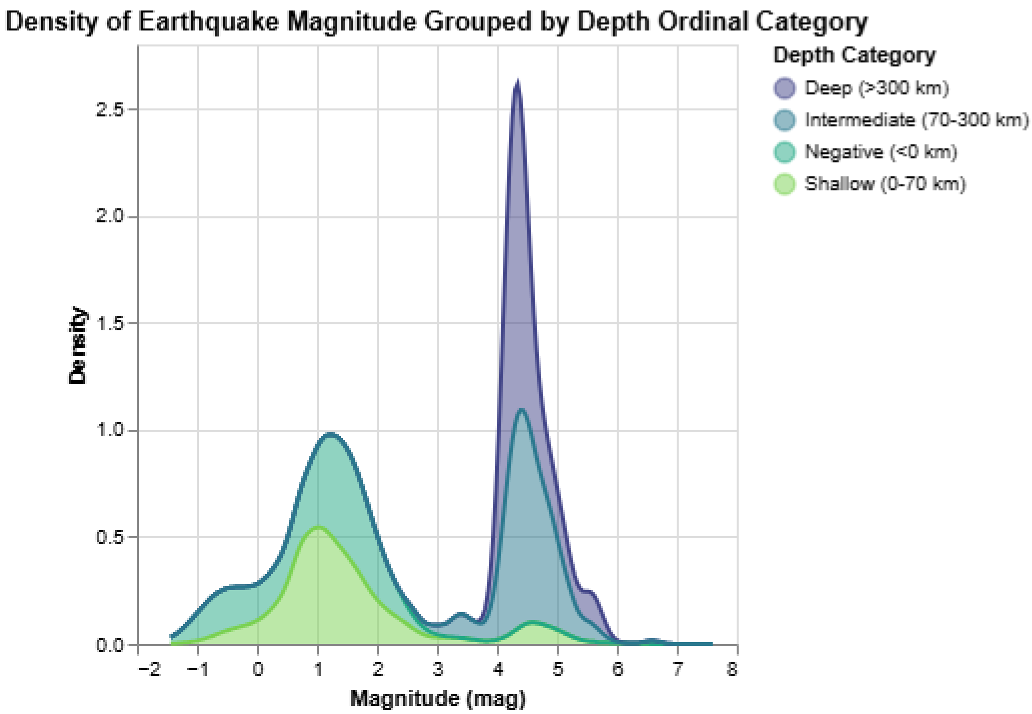
The overwhelming majority of the data points are clustered between 0 km and 100 km depth. The density of points drops off dramatically after 100 km.

This confirms that most earthquakes, regardless of magnitude, occur in the Earth's brittle upper crust and lithosphere where rocks are cold and rigid enough to store and release elastic strain energy. This is a fundamental concept in seismology.

In [21]:

```
depth_density_chart = alt.Chart(df).transform_density(
    'mag',
    groupby=['depth_ordinal'],
    as_=['mag', 'density']
).mark_area(
    opacity=0.5,
    line={'color':'darkgrey'}
).encode(
    x=alt.X('mag:Q', title='Magnitude (mag)'),
    y=alt.Y('density:Q', title='Density'),

    color=alt.Color('depth_ordinal:N', title='Depth Category', scale=alt.Scale(sche

    tooltip=[
        alt.Tooltip('depth_ordinal:N', title='Depth Category'),
        alt.Tooltip('mag:Q', title='Magnitude'),
        alt.Tooltip('density:Q', title='Density')
    ]
).properties(
    title='Density of Earthquake Magnitude Grouped by Depth Ordinal Category'
)

depth_density_chart
```

Out[21]:



1. Shallow (0-70 km)

Distribution: This category (light green) has a bimodal distribution.

It has a large peak at low magnitudes, roughly M≈1.5, representing the vast number of small, local crustal earthquakes.

It has a smaller, but significant, peak centered around M≈4.5, representing the moderate-to-large shallow earthquakes.

Significance: Because it encompasses the Earth's brittle crust, the Shallow category covers the fullest range of magnitudes from negative values up to M≈7.5. Shallow earthquakes are the most destructive.

2. Deep (≥300 km)

Distribution: The Deep category (dark blue/purple) shows a remarkably narrow and highly peaked distribution centered sharply around M≈4.5.

Significance:

The peak is the highest of all categories, meaning that when a deep earthquake does occur, its magnitude is very likely to be close to M4.5.

There are no micro-earthquakes (M < 2) and the maximum magnitude is lower (barely reaching M 6). This confirms the geophysical constraint that very large earthquakes cannot happen at great depths due to high heat and pressure making rocks less brittle.

3. Intermediate (70-300 km)

Distribution: The Intermediate category (teal) mostly mirrors the Shallow distribution but is heavily weighted towards the low-magnitude peak (M≈1.5) and significantly contributes to the M≈4.5 peak.

Significance: These earthquakes occur in the subducting slab as it descends into the mantle. The distribution shows they still generate many small quakes, but their large-magnitude potential begins to drop off compared to the Shallow layer.

4. Negative (< 0 km)

Distribution: This category (light gray) is the smallest overall area but confirms the existence of highly sensitive recordings. It contributes mostly to the micro-earthquake end (M<1.0), reflecting data from extremely sensitive regional networks.

Significance: Earthquakes technically cannot happen above 0 km. This category represents the highest-quality, highest-sensitivity measurements, often involving very precise techniques (like double-difference relocation) where small tremors are assigned negative magnitudes due to their calculated position relative to a reference point or depth.

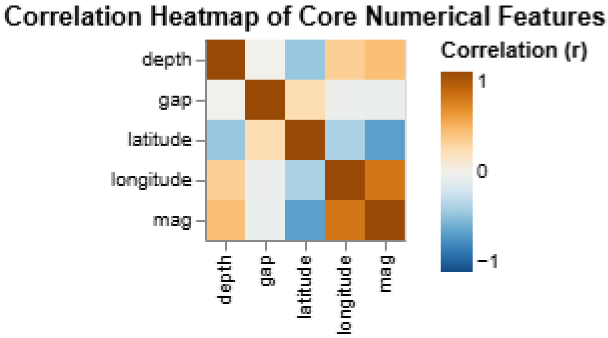
In [22]:
```
corr_matrix_focused = df[core_cols].corr()
cor_data_focused = corr_matrix_focused.stack().reset_index()
cor_data_focused = cor_data_focused.rename(columns={
    0: 'correlation',
    'level_0': 'variable1',
    'level_1': 'variable2'
})
corr_matrix_focused
```

Out[22]:

	mag	depth	gap	latitude	longitude
mag	1.000000	0.397189	-0.056169	-0.607594	0.733623
depth	0.397189	1.000000	0.001089	-0.413894	0.305163
gap	-0.056169	0.001089	1.000000	0.218426	-0.036150
latitude	-0.607594	-0.413894	0.218426	1.000000	-0.348001
longitude	0.733623	0.305163	-0.036150	-0.348001	1.000000

In [23]:
```
cor_data_focused['correlation_label'] = cor_data_focused['correlation'].map('{:.2f}

correlation_heatmap = alt.Chart(cor_data_focused).mark_rect().encode(
    alt.X('variable1:O', title=''),
    alt.Y('variable2:O', title=''),
    alt.Color('correlation', scale=alt.Scale(scheme='blueorange', domain=[-1, 1]),
    text=alt.Text('correlation_label:N'),
    tooltip=['variable1', 'variable2', 'correlation_label']
).properties(
    title='Correlation Heatmap of Core Numerical Features'
).interactive()
correlation_heatmap
```

Out[23]:



There is a strong correlation between longttdue vs mag and latitude vs mag. Let's dive deeper to understand the distribution of earthquakes based on regions.

In [24]:

```
from vega_datasets import data

world = alt.topo_feature(data.world_110m.url, 'countries')

background_map = alt.Chart(world).mark_geoshape(
    fill='lightgray',
    stroke='white'
).project(
    "equirectangular"
).properties(
    width=700,
    height=400
)
```

In [25]:

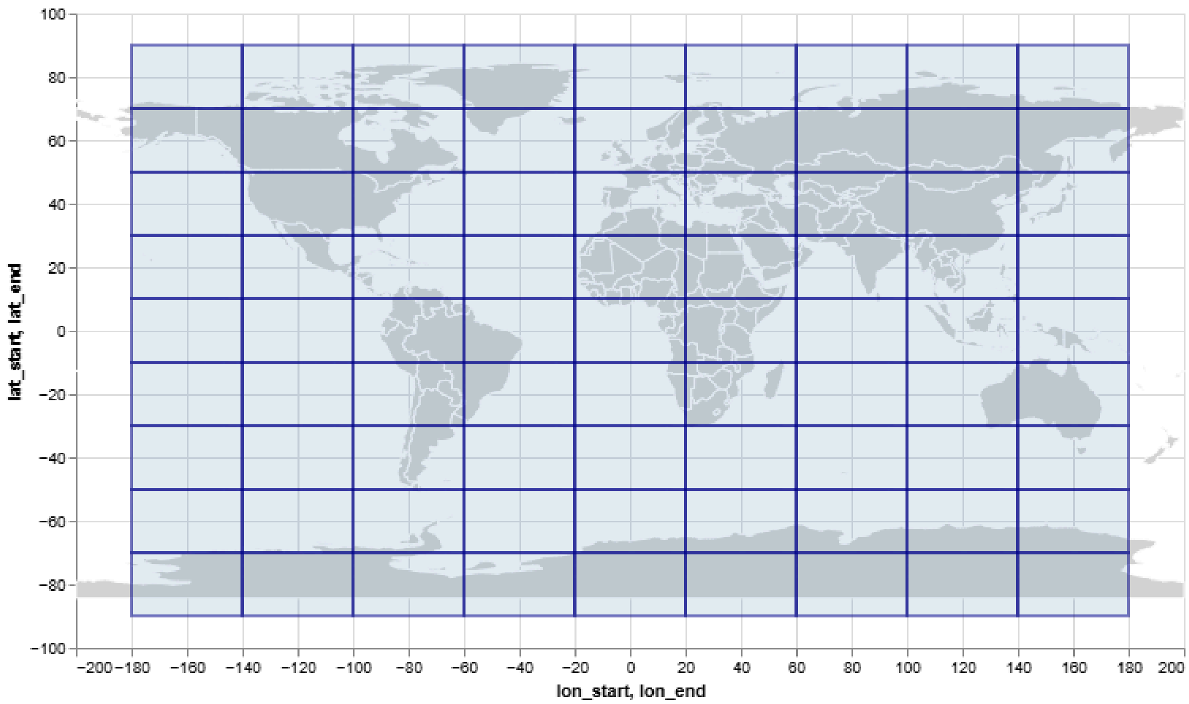
```
import pandas as pd
import numpy as np

lon_step = 40   # wider grid blocks
lat_step = 20

lon_edges = np.arange(-180, 180, lon_step)
lat_edges = np.arange(-90, 90, lat_step)

grid = pd.DataFrame([
    {
        "lon_start": lon,
        "lon_end": lon + lon_step,
        "lat_start": lat,
        "lat_end": lat + lat_step
    }
    for lon in lon_edges
    for lat in lat_edges
])

grid_chart = alt.Chart(grid).mark_rect(
    fill='steelblue',
    fillOpacity=0.15,
    stroke='darkblue',
    strokeWidth=1
).encode(
    x='lon_start:Q',
```

```
    x2='lon_end:Q',
    y='lat_start:Q',
    y2='lat_end:Q',
    tooltip=['lon_start', 'lon_end', 'lat_start', 'lat_end']
).project(
    type="equirectangular"  # same projection as map
)
```

The following is the grid we created for the binning approach:

In [26]:
```
map_with_grid = background_map + grid_chart
map_with_grid
```

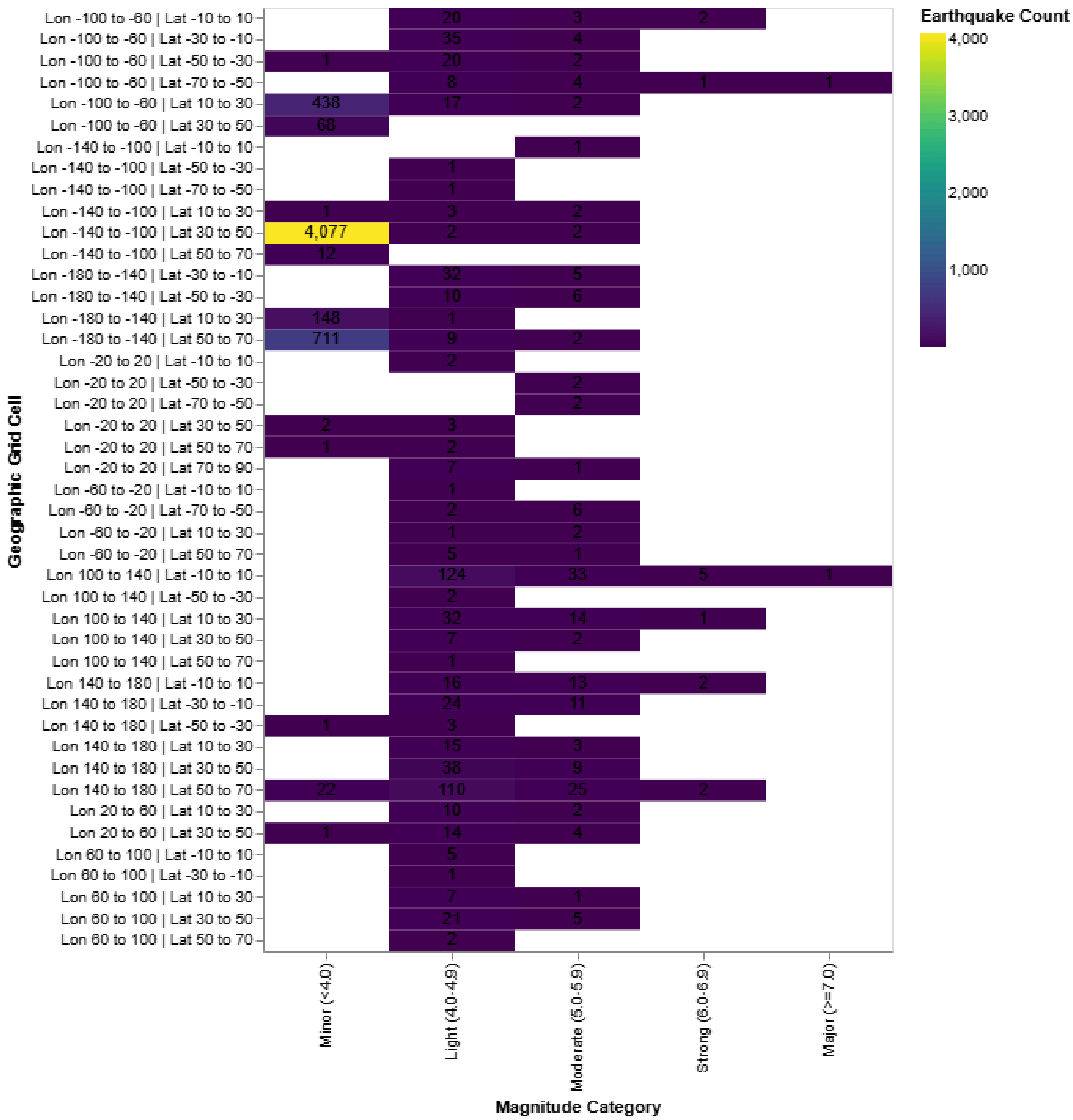
Out[26]:



In [27]:
```
lon_step = 40
lat_step = 20

df['lon_bin'] = np.floor((df['longitude'] + 180) / lon_step) * lon_step - 180
df['lat_bin'] = np.floor((df['latitude'] + 90) / lat_step) * lat_step - 90

df['grid_label'] = (
    'Lon ' + df['lon_bin'].astype(int).astype(str) +
    ' to ' + (df['lon_bin'] + lon_step).astype(int).astype(str) +
    ' | Lat ' + df['lat_bin'].astype(int).astype(str) +
    ' to ' + (df['lat_bin'] + lat_step).astype(int).astype(str)
)

def categorize_magnitude(m):
    if m < 4.0:
        return 'Minor (<4.0)'
    elif m < 5.0:
        return 'Light (4.0-4.9)'
    elif m < 6.0:
        return 'Moderate (5.0-5.9)'
    elif m < 7.0:
```

```
        return 'Strong (6.0-6.9)'
    else:
        return 'Major (>=7.0)'

df['mag_ordinal'] = df['mag'].apply(categorize_magnitude)
mag_order = ['Minor (<4.0)', 'Light (4.0-4.9)', 'Moderate (5.0-5.9)', 'Strong (6.0-

grid_summary = (
    df.groupby(['grid_label', 'mag_ordinal'])
    .size()
    .reset_index(name='count')
)

heatmap = alt.Chart(grid_summary).mark_rect().encode(
    x=alt.X('mag_ordinal:O', sort=mag_order, title='Magnitude Category'),
    y=alt.Y('grid_label:N', title='Geographic Grid Cell'),
    color=alt.Color('count:Q', scale=alt.Scale(scheme='viridis'), title='Earthquake
    tooltip=['grid_label', 'mag_ordinal', alt.Tooltip('count:Q', title='Count')]
)

text = heatmap.mark_text().encode(
    text=alt.Text('count:Q', format=',.0f'),
    color=alt.value('black')
)

final_heatmap_grid = (heatmap + text).properties(width=400, height=600)
final_heatmap_grid
```

Out[27]:



High Sensitivity vs. True Activity: The cell Lon -140 to -100, Lat 30 to 50 (4,077 minor quakes) has the highest count. This is a region (like California) with high tectonic activity and an extremely dense seismic network, allowing for the detection of many more minor quakes compared to less instrumented regions.

Relative Hazard: While the overall counts are dominated by Minor quakes, the cells with the most quakes in the Moderate (5.0-5.9) and Strong (6.0-6.9) categories (e.g., Lon 100-140) indicate the areas with the highest frequency of potentially damaging events.

Summary

Feature Relationships and Data Quality

Network Source Impact: Most networks display similar magnitude distributions, but the US network stands out with a higher number of outliers, likely because it records a greater volume of earthquakes globally and has an extremely dense seismic network.

Data Quality for Major Events: The optimal data quality measures (gap levels of moderate-high and high) account for nearly all the Moderate (5.0-5.9) and Strong (6.0-6.9) magnitude quakes, indicating high confidence in the data collected for the most significant events.

Negative Depth Quakes: Earthquakes categorized with a Negative (<0 km) depth are predominantly Minor (<4.0) in magnitude. This reflects the high sensitivity of regional networks, as negative depth values often result from precise relocation techniques relative to a reference point.

Quantitative Relationships

The correlation analysis highlighted significant relationships among core numerical features:

Magnitude and Longitude: There is a strong positive correlation (0.73).

Magnitude and Latitude: There is a strong negative correlation (-0.61).

Depth and Magnitude: A moderate positive correlation (0.40) exists between depth and magnitude.

Depth and Latitude: A moderate negative correlation (-0.41) exists between depth and latitude.

Spatial Distribution and Seismic Hazard

Depth Concentration: Earthquakes are primarily concentrated at shallow (0-70 km) and intermediate (70-300 km) depths. The deeper categories (Intermediate and Deep >300 km) contain nearly all the higher magnitude events (Moderate, Strong, and Major), supporting the observation that deeper quakes are generally of higher magnitude.

Geographic Hazard Concentration: The potential for severe seismic hazard (higher proportion of Strong and Major quakes) is concentrated geographically at the extremes of the sampled latitude range (high northern and high southern latitudes), corresponding to major plate boundaries like the Circum-Pacific Belt. The longitude range 100-140 showed the highest frequency of potentially damaging events in the Moderate and Strong categories.