E-Commerce Event Funnel Analysis and Revenue Prediction

August 10, 2025

[3]:
```
!pip install -q kaggle
```

[4]:
```
import os
os.environ["KAGGLE_CONFIG_DIR"] = r"C:\Users\zheng\.kaggle"
```

[5]:
```
import zipfile, os, glob, shutil, pathlib, subprocess, sys

datasets = [
    "mkechinov/ecommerce-behavior-data-from-multi-category-store",
    "mkechinov/ecommerce-purchase-history-from-electronics-store",
    "mkechinov/ecommerce-events-history-in-cosmetics-shop",
    "mkechinov/ecommerce-purchase-history-from-jewelry-store",
    "mkechinov/ecommerce-events-history-in-electronics-store"
]

os.makedirs("input", exist_ok=True)

for ds in datasets:
    slug = ds.split("/",1)[1]
    outdir = f"input/{slug}"
    os.makedirs(outdir, exist_ok=True)
    print("↓ downloading:", ds)
    subprocess.run(["kaggle","datasets","download","-d",ds,"-p",outdir,"-q"],␣
 ↪check=True)
    # unzip
    for z in glob.glob(f"{outdir}/*.zip"):
        print("  unzip:", os.path.basename(z))
        with zipfile.ZipFile(z) as f:
            f.extractall(outdir)
        os.remove(z)

print("done. some samples:", glob.glob("input/**/*.csv", recursive=True)[:5])
```

```
↓ downloading: mkechinov/ecommerce-behavior-data-from-multi-category-store
  unzip: ecommerce-behavior-data-from-multi-category-store.zip
↓ downloading: mkechinov/ecommerce-purchase-history-from-electronics-store
  unzip: ecommerce-purchase-history-from-electronics-store.zip
↓ downloading: mkechinov/ecommerce-events-history-in-cosmetics-shop
```

```
  unzip: ecommerce-events-history-in-cosmetics-shop.zip
↓ downloading: mkechinov/ecommerce-purchase-history-from-jewelry-store
  unzip: ecommerce-purchase-history-from-jewelry-store.zip
↓ downloading: mkechinov/ecommerce-events-history-in-electronics-store
  unzip: ecommerce-events-history-in-electronics-store.zip
done. some samples: ['input\\ecommerce-behavior-data-from-multi-category-
store\\2019-Nov.csv', 'input\\ecommerce-behavior-data-from-multi-category-
store\\2019-Oct.csv', 'input\\ecommerce-events-history-in-cosmetics-
shop\\2019-Dec.csv', 'input\\ecommerce-events-history-in-cosmetics-
shop\\2019-Nov.csv', 'input\\ecommerce-events-history-in-cosmetics-
shop\\2019-Oct.csv']
```

[6]:

```python
import pandas as pd, numpy as np, glob, os, pathlib, uuid

WAREHOUSE = "warehouse"
os.makedirs(WAREHOUSE, exist_ok=True)

WANT = ["event_time","event_type","order_id","product_id","category_id",
        "category_code","brand","price","user_id","user_session"]

def normalize_chunk(df: pd.DataFrame) -> pd.DataFrame:
    df.columns = [c.strip().lower() for c in df.columns]
    keep = [c for c in WANT if c in df.columns]
    if not keep:
        return pd.DataFrame()
    df = df[keep].copy()


    rename = {
        "event_time":"time","event_type":"event","product_id":"product",
        "category_code":"category","price":"price","user_id":"user_id"
    }
    for k,v in rename.items():
        if k in df.columns: df.rename(columns={k:v}, inplace=True)

    if "time" in df.columns:
        df["time"] = pd.to_datetime(df["time"].astype(str).str.replace("␣
↪UTC","", regex=False),
                                    errors="coerce")
        df["hour"] = df["time"].dt.hour
        df["date"] = df["time"].dt.date
    if "price" in df.columns:
        df["price"] = pd.to_numeric(df["price"].astype(str).str.replace(r"[,$␣
↪]","", regex=True),
                                    errors="coerce")
    return df
```

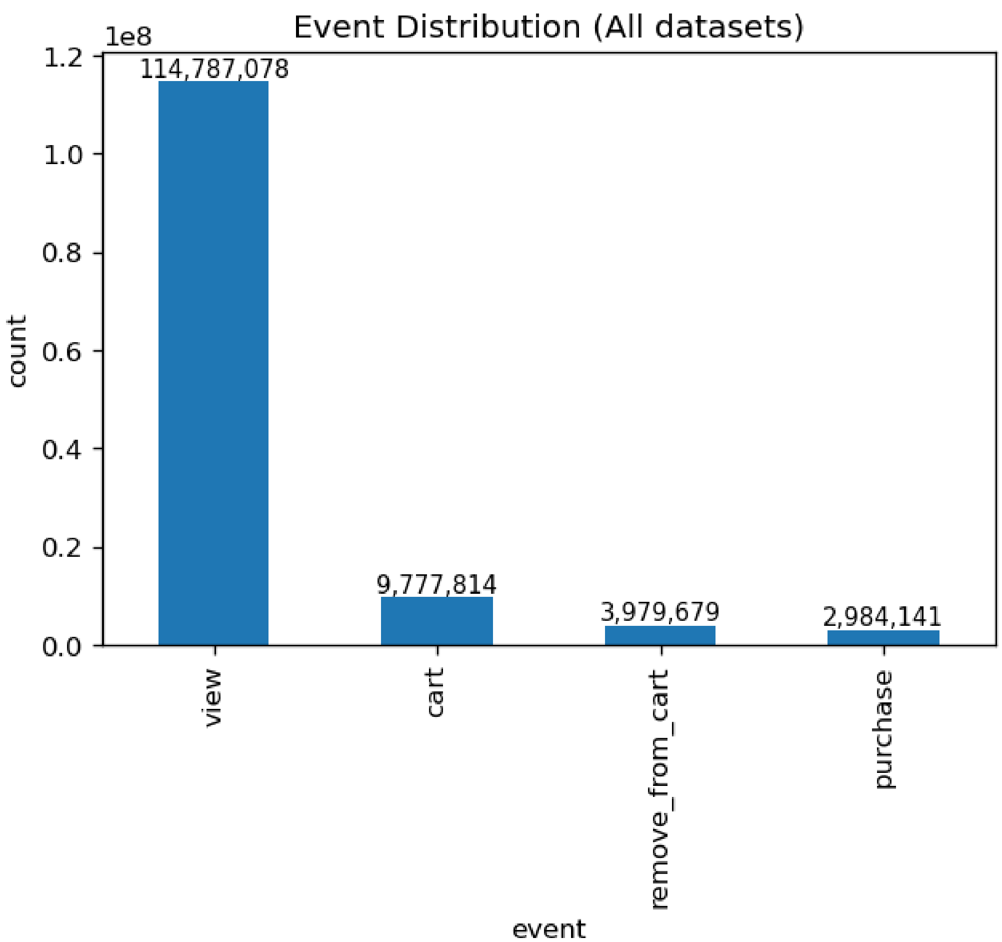
```python
csv_files = glob.glob("input/**/*.csv", recursive=True)
print("CSV files:", len(csv_files))

rows_written = 0
for p in csv_files:
    dataset = pathlib.Path(p).parts[1]
    out_dir  = f"{WAREHOUSE}/dataset={dataset}"
    os.makedirs(out_dir, exist_ok=True)

    for i,chunk in enumerate(pd.read_csv(p, chunksize=500_000,␣
 ↪low_memory=False, dtype=str, on_bad_lines="skip")):
        chunk = normalize_chunk(chunk)
        if chunk.empty:
            continue
        chunk["dataset"] = dataset
        chunk["source_file"] = os.path.basename(p)

        out_path = f"{out_dir}/part_{i:04d}_{uuid.uuid4().hex[:8]}.parquet"
        chunk.to_parquet(out_path, index=False)
        rows_written += len(chunk)

print(f"  Thers are {rows_written:,} rows → {WAREHOUSE}")
```

```
CSV files: 10
   134,162,233  → warehouse
```

[25]:
```python
import matplotlib.pyplot as plt
plt.rcParams["figure.dpi"] = 120

files = glob.glob(f"{WAREHOUSE}/dataset=*/*.parquet")
print("parquet parts:", len(files))
read_cols = ["time","event","brand","price","hour","dataset"]

from collections import Counter
event_by_hour = None
brand_counts = Counter()
price_bins = np.linspace(0, 2000, 101)
price_hist = np.zeros(len(price_bins)-1, dtype=float)

for f in files:
    df = pd.read_parquet(f, columns=[c for c in read_cols if c in pd.
 ↪read_parquet(f).columns])
    # 1) hour × event
    if set(["hour","event"]).issubset(df.columns):
        tmp = df.groupby(["hour","event"]).size().unstack(fill_value=0)
        event_by_hour = tmp if event_by_hour is None else event_by_hour.
 ↪add(tmp, fill_value=0)
```

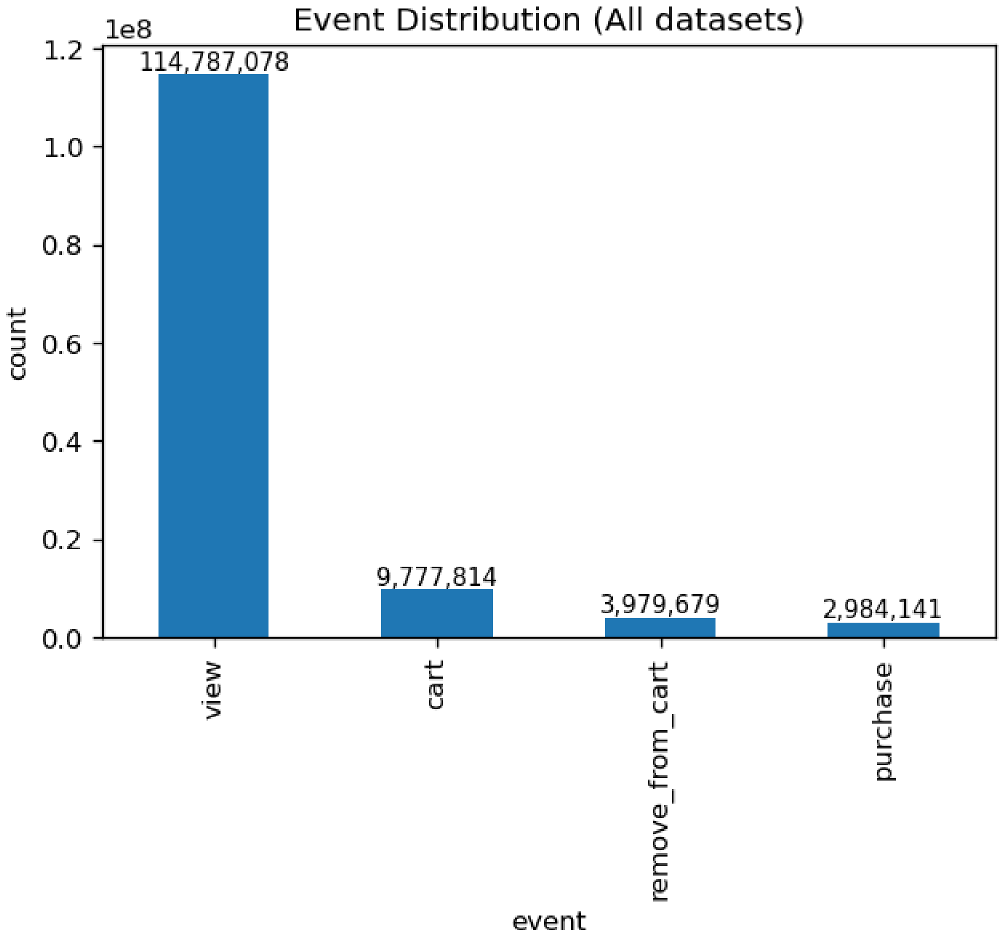
```python
    # 2) brand
    if "brand" in df.columns:
        brand_counts.update(df["brand"].dropna())
    # 3) price histogram
    if "price" in df.columns:
        arr = pd.to_numeric(df["price"], errors="coerce").dropna().to_numpy()
        arr = arr[arr <= price_bins[-1]]
        if arr.size:
            h,_ = np.histogram(arr, bins=price_bins)
            price_hist += h
```

```
parquet parts: 274
```



[38]:
```python
# event distribution
if event_by_hour is not None:
    event_total = event_by_hour.sum(axis=0).sort_values(ascending=False)
```

```python
ax = event_total.plot(kind='bar', figsize=(6,4), title="Event Distribution (All datasets)")
ax.set_xlabel("event"); ax.set_ylabel("count")

for i,v in enumerate(event_total):
    ax.text(i, v, f"{int(v):,}", ha='center', va='bottom', fontsize=9)
plt.show()
```



##Event Distribution Analysis

From the combined datasets: 1. View events dominate with ~114.8 million occurrences, far exceeding other event types. This indicates extremely high user browsing activity, but the majority of views do not lead to further engagement. 2. Cart additions occur ~9.78 million times, meaning only about 8.52% of views convert into a cart action. 3. Remove-from-cart events (~3.98 million) are notable compared to total cart actions, showing drop-offs in the purchase funnel. 4. Purchases total ~2.98 million, giving a view-to-purchase conversion rate of roughly 2.60%. 5. The cart-to-purchase conversion rate is 30.52%, indicating a relatively efficient checkout process once items are added to the cart.

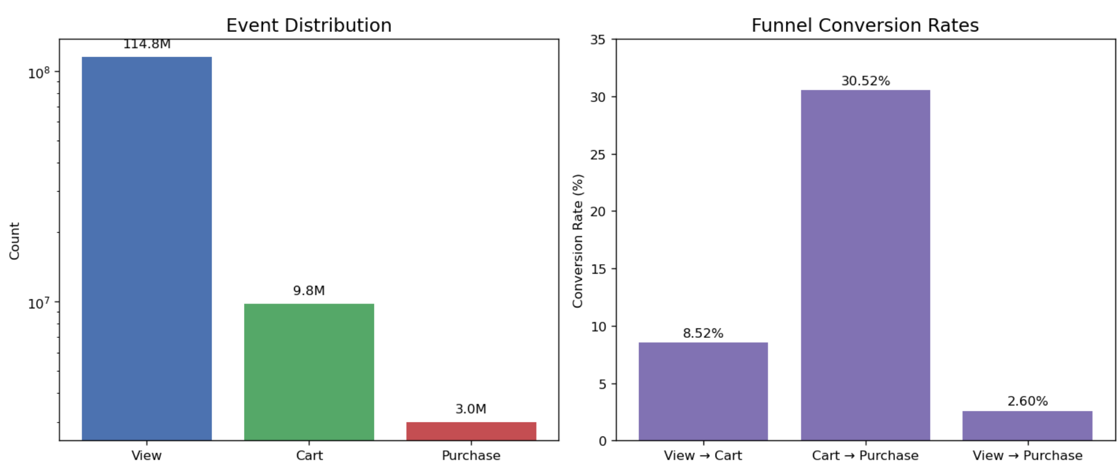
Key Insight: The large gap between views and purchases suggests opportunities to improve conversion performance — for example, enhancing product descriptions, streamlining the add-to-cart process, and offering targeted incentives to reduce cart abandonment.

[26]:
```
cart_like = [c for c in hour_df.columns if c.lower() in {"cart", "add_to_cart"}]
if len(cart_like) > 1:
    hour_df["cart"] = hour_df[cart_like].sum(axis=1)
elif "cart" not in hour_df.columns and cart_like:
    hour_df["cart"] = hour_df[cart_like[0]]

tot = hour_df[["view", "cart", "purchase"]].sum()
view = float(tot.get("view", 0))
cart = float(tot.get("cart", 0))
purchase = float(tot.get("purchase", 0))

view_to_cart      = cart / view if view > 0 else np.nan
cart_to_purchase  = purchase / cart if cart > 0 else np.nan
view_to_purchase  = purchase / view if view > 0 else np.nan

print(f"view   total: {view:,.0f}")
print(f"cart   total: {cart:,.0f}")
print(f"purchase total: {purchase:,.0f}\n")

print(f"View -> Cart:      {view_to_cart:,.2%}")
print(f"Cart -> Purchase:  {cart_to_purchase:,.2%}")
print(f"View -> Purchase:  {view_to_purchase:,.2%}")
```

```
view   total: 114,787,078
cart   total: 9,777,814
purchase total: 2,984,141

View -> Cart:      8.52%
Cart -> Purchase:  30.52%
View -> Purchase:  2.60%
```

[51]:
```
events = ["View", "Cart", "Purchase"]
counts = [114_787_078, 9_777_814, 2_984_141]



view_to_cart = counts[1] / counts[0] * 100
cart_to_purchase = counts[2] / counts[1] * 100
view_to_purchase = counts[2] / counts[0] * 100

fig, axes = plt.subplots(1, 2, figsize=(12, 5))



axes[0].bar(events, counts, color=["#4C72B0", "#55A868", "#C44E52"])
axes[0].set_title("Event Distribution", fontsize=14)
```

```
axes[0].set_ylabel("Count")
axes[0].set_yscale("log")
for i, v in enumerate(counts):
    axes[0].text(i, v*1.1, f"{v/1e6:.1f}M", ha="center", fontsize=10)


funnel_stages = ["View → Cart", "Cart → Purchase", "View → Purchase"]
funnel_rates = [view_to_cart, cart_to_purchase, view_to_purchase]

axes[1].bar(funnel_stages, funnel_rates, color="#8172B3")
axes[1].set_ylim(0, 35)
axes[1].set_title("Funnel Conversion Rates", fontsize=14)
axes[1].set_ylabel("Conversion Rate (%)")
for i, v in enumerate(funnel_rates):
    axes[1].text(i, v+0.5, f"{v:.2f}%", ha="center", fontsize=10)

out_dir = "figs"
os.makedirs(out_dir, exist_ok=True)
fname = os.path.join(out_dir, "event_distribution_funnel.png")

plt.tight_layout()
plt.savefig(fname, dpi=300, bbox_inches="tight")
plt.show()

print("Image saved to:", os.path.abspath(fname))
```

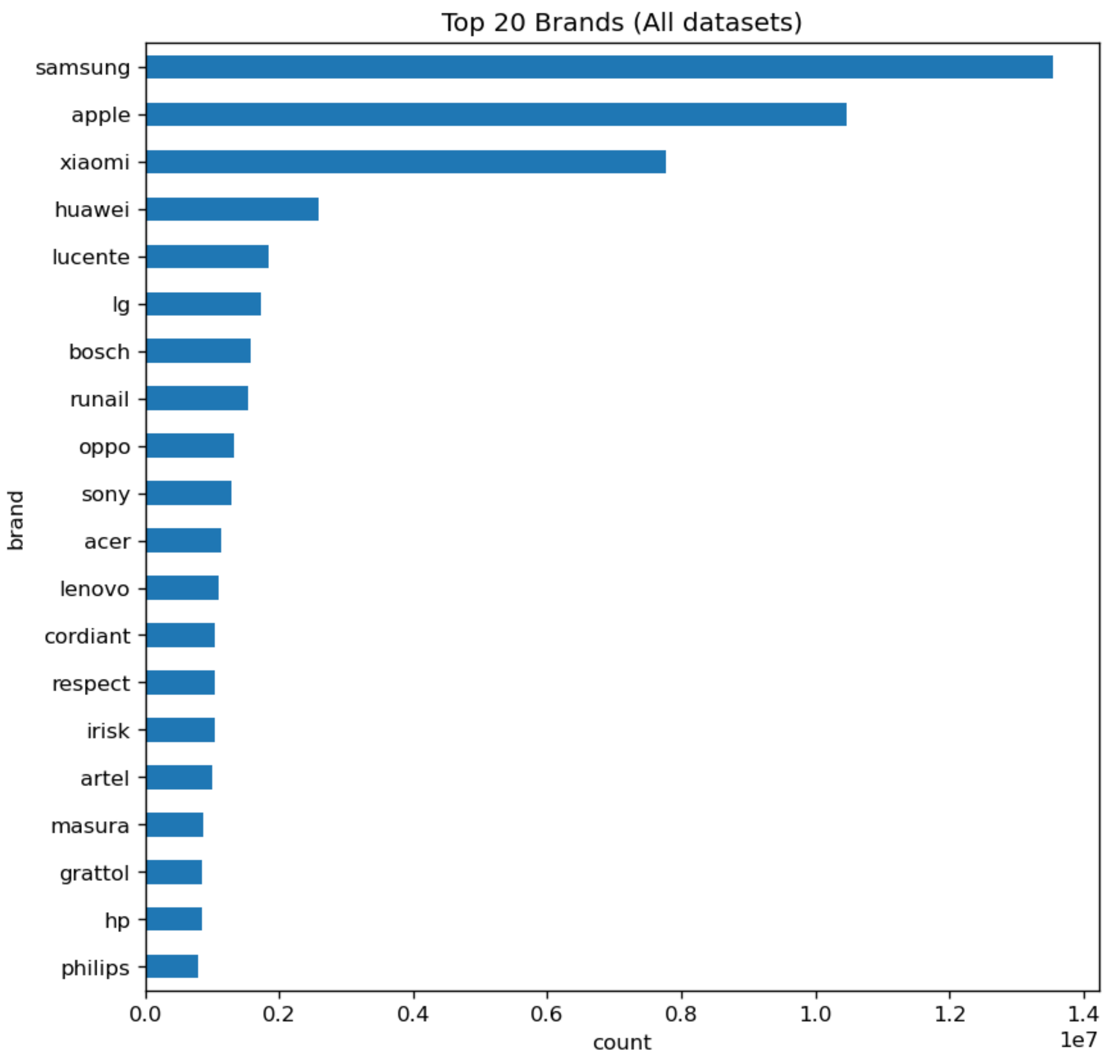



```
Image saved to: C:\Users\zheng\figs\event_distribution_funnel.png
```

View total: 114,787,078 Cart total: 9,777,814 Purchase total: 2,984,141

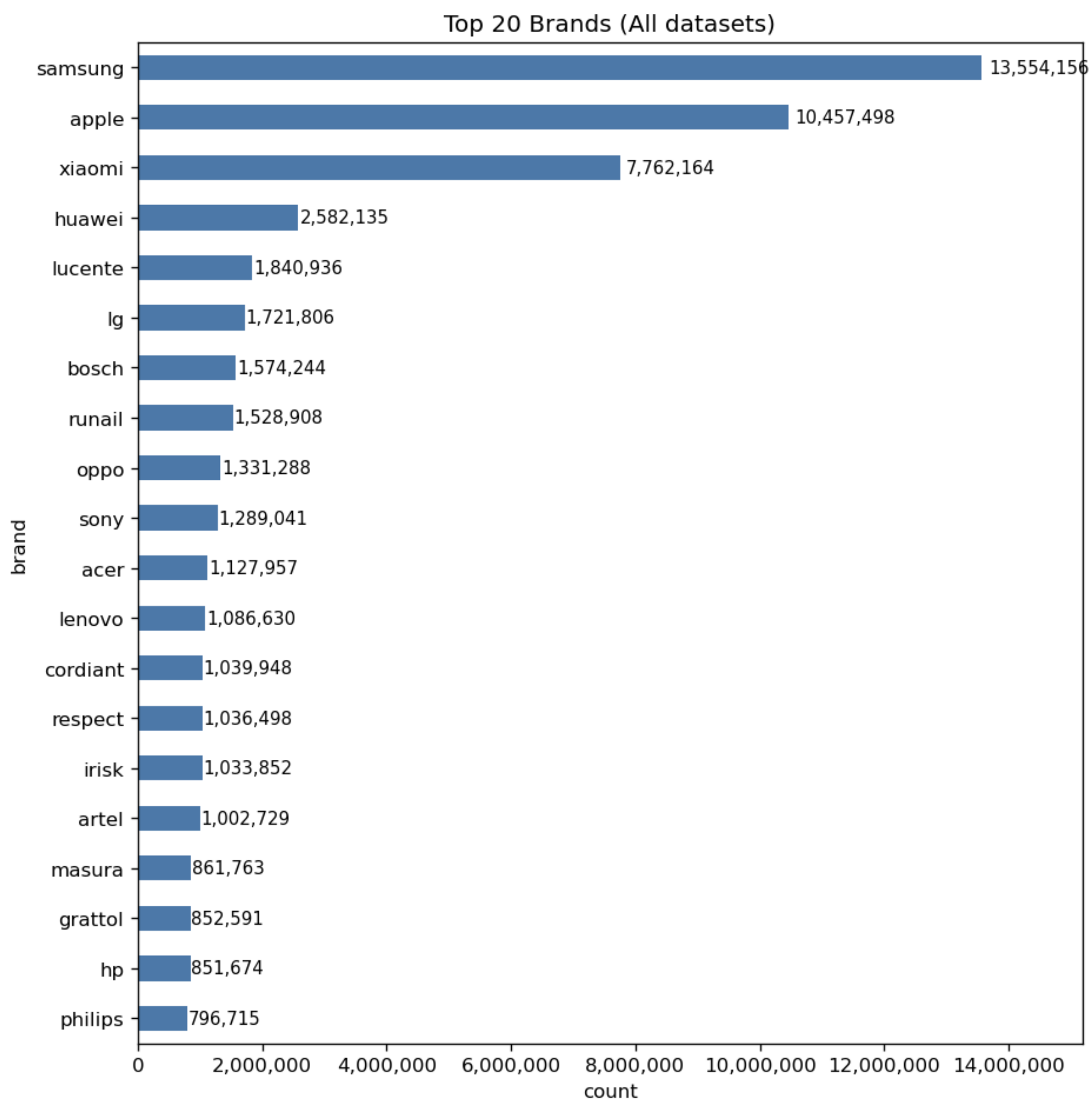
View → Cart: 8.52% Low proportion of views leading to cart additions, indicating potential to improve product page engagement. Cart → Purchase: 30.52% Strong checkout conversion rate, suggesting the purchasing process is relatively smooth. View → Purchase: 2.60% Overall view-to-purchase rate is low, showing significant room for conversion optimization.

[27]:
```
#  brand Top 20
top20 = pd.Series(brand_counts).sort_values(ascending=False).head(20).
 ↪sort_values()
plt.figure(figsize=(8,8))
top20.plot(kind="barh")
plt.title("Top 20 Brands (All datasets)")
plt.xlabel("count"); plt.ylabel("brand")
plt.show()
```

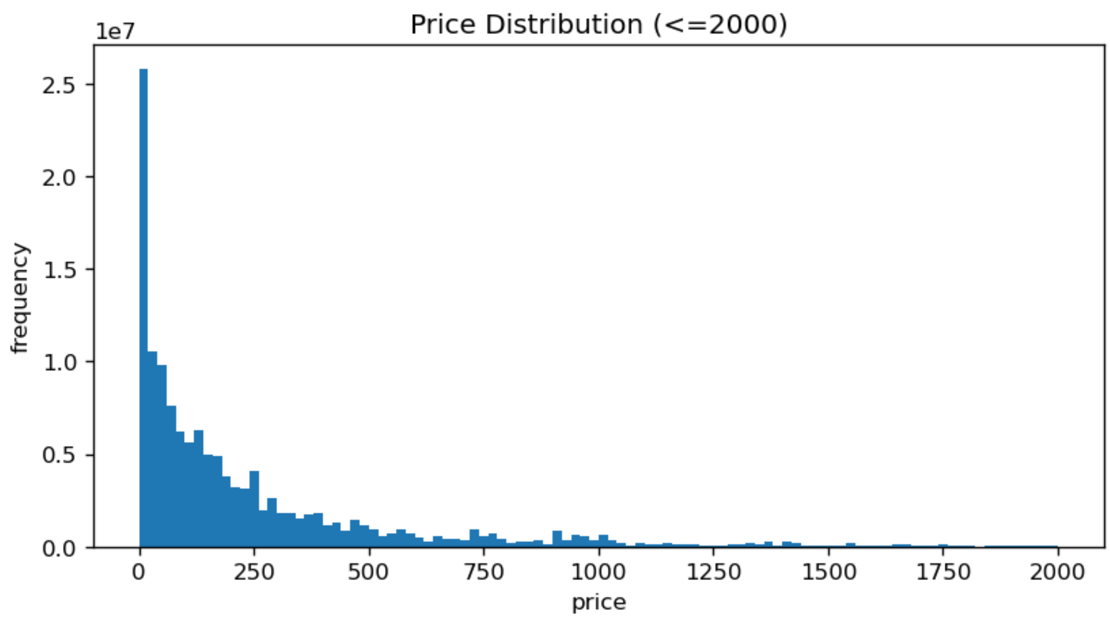


[28]:
```
# top20: Series index=brand values=count
top20 = (pd.Series(brand_counts)
```

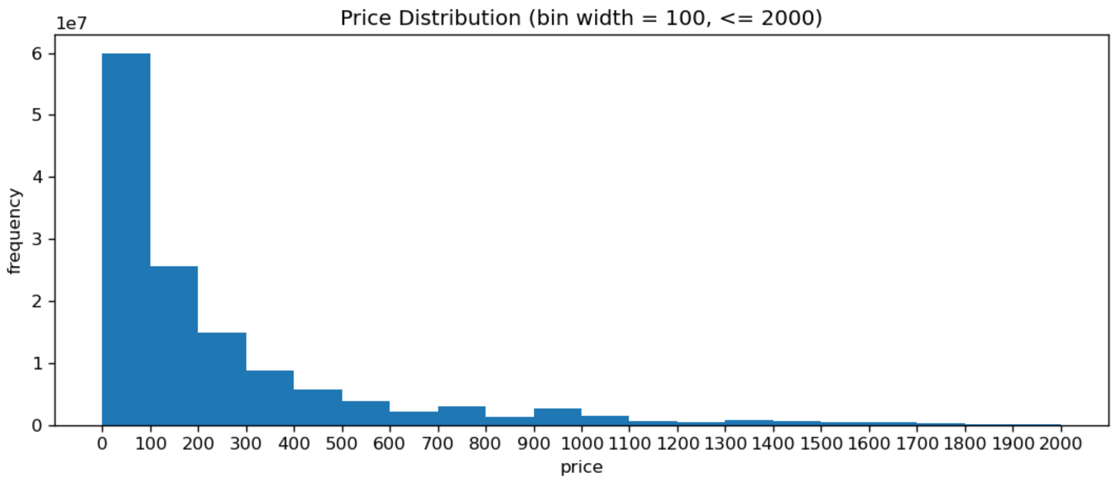
```
         .dropna()
         .astype(int)
         .sort_values(ascending=False)
         .head(20)
         .sort_values())

fig, ax = plt.subplots(figsize=(8, 8))
top20.plot(kind='barh', ax=ax, color='#4C78A8')

ax.set_title("Top 20 Brands (All datasets)")
ax.set_xlabel("count")
ax.set_ylabel("brand")

from matplotlib.ticker import StrMethodFormatter
ax.xaxis.set_major_formatter(StrMethodFormatter('{x:,.0f}'))

xmax = top20.max()
ax.set_xlim(0, xmax * 1.12)
for y, v in enumerate(top20.values):
    ax.text(v * 1.01, y, f"{v:,.0f}", va='center', ha='left', fontsize=9)

plt.tight_layout()
plt.show()
```



[29]:
```
#  price distribution
centers = (price_bins[:-1] + price_bins[1:]) / 2
widths  = (price_bins[1:] - price_bins[:-1])
plt.figure(figsize=(8,4))
plt.bar(centers, price_hist, width=widths, align="center")
plt.title("Price Distribution (<=2000)")
plt.xlabel("price"); plt.ylabel("frequency")
plt.show()
```

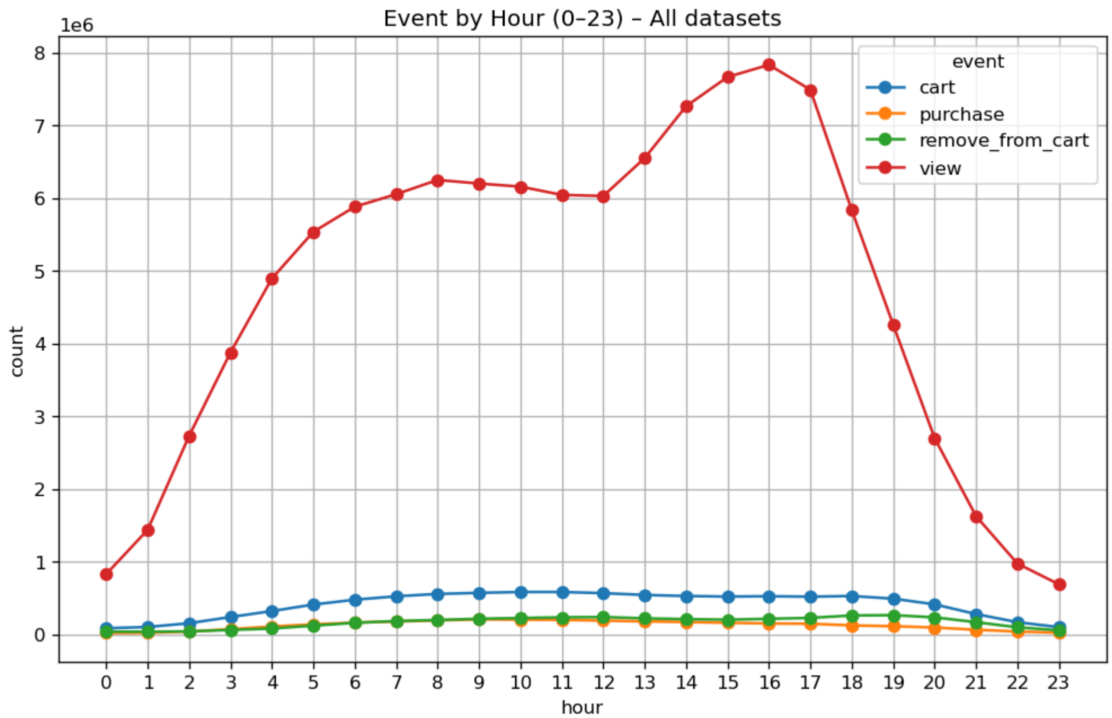


[35]:
```
prices = []
for f in files:
    tmp = pd.read_parquet(f, columns=["price"])
    prices.append(pd.to_numeric(tmp["price"], errors="coerce"))

p = pd.concat(prices, ignore_index=True).dropna()
p = p[(p >= 0) & (p <= 2000)]

# 20  bins
price_bins = np.arange(0, 2000 + 100, 100)
price_hist, edges = np.histogram(p, bins=price_bins)

centers = (edges[:-1] + edges[1:]) / 2
widths  = np.diff(edges)

plt.figure(figsize=(9,4))
plt.bar(centers, price_hist, width=widths, align="center")
plt.title("Price Distribution (bin width = 100, <= 2000)")
plt.xlabel("price")
plt.ylabel("frequency")
plt.xticks(price_bins)
plt.tight_layout()
plt.show()

print("bins =", len(price_bins)-1)
```




```
bins = 20
```

[36]:
```
#  events in hours
if event_by_hour is not None:
    event_by_hour = event_by_hour.reindex(range(24), fill_value=0).sort_index()
    ax = event_by_hour.plot(marker='o', figsize=(10,6))
    ax.set_title("Event by Hour (0-23) - All datasets")
    ax.set_xlabel("hour"); ax.set_ylabel("count"); ax.set_xticks(range(24)); ax.
 ↪grid(True)
    plt.show()
```



- View activity peaks twice: late morning (9–11 AM) and late afternoon (4–5 PM), with the highest spike around **5 PM**.
- Cart, purchase, and remove-from-cart** events follow a similar pattern to views, but remain much lower in absolute volume.
- Activity is lowest between midnight and 5 AM, then steadily rises after 6 AM.
- The alignment between view peaks and purchase/cart peaks suggests that user buying intent is closely tied to browsing volume.

Insight: **Marketing campaigns or promotions could be scheduled around the** late morning** and **late afternoon** peaks to maximize conversions.

[37]:
```
WAREHOUSE = "warehouse"
parts = glob.glob(os.path.join(WAREHOUSE, "dataset=*/*.parquet"))


if not parts:
    raise RuntimeError("no parquet put CSVs into warehouse/).")

print("number of parts ", len(parts))

hourly_counts = {}   # {hour_ts: {'view':x,'cart':y,'purchase':z,...}}
hourly_revenue = {}  # {hour_ts: revenue}

use_cols = ["time","event","price"]
```

```
for f in parts:
    df = pd.read_parquet(f, columns=[c for c in use_cols if c in pd.
 ↪read_parquet(f).columns])

    if "time" not in df.columns or "event" not in df.columns:
        continue
    df["time"] = pd.to_datetime(df["time"], errors="coerce")
    df = df.dropna(subset=["time","event"])

    df["hour_ts"] = df["time"].dt.floor("h")

    cnt = df.groupby(["hour_ts","event"]).size().unstack(fill_value=0)

    # revenue only price with purchase
    revenue = None
    if "price" in df.columns:
        df["price"] = pd.to_numeric(df["price"], errors="coerce")
        revenue = df.loc[df["event"].str.lower().eq("purchase"),␣
 ↪["hour_ts","price"]] \
                    .groupby("hour_ts")["price"].sum().rename("revenue")

    for ts, row in cnt.iterrows():
        hourly_counts.setdefault(ts, {})
        for ev, v in row.items():
            hourly_counts[ts][ev] = hourly_counts[ts].get(ev, 0) + int(v)

    if revenue is not None:
        for ts, val in revenue.items():
            hourly_revenue[ts] = hourly_revenue.get(ts, 0.0) + float(val)


counts_df = pd.DataFrame.from_dict(hourly_counts, orient="index").sort_index().
 ↪fillna(0).astype(int)
revenue_df = pd.Series(hourly_revenue, name="revenue").to_frame()
hour_df = counts_df.join(revenue_df, how="outer").fillna(0)


for col in ["view","cart","purchase"]:
    if col not in hour_df.columns:
        hour_df[col] = 0

hour_df.head()
```

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[37]:

	cart	purchase	view	remove_from_cart	revenue
2019-10-01 00:00:00	419	189	1585	348	3136.04
2019-10-01 01:00:00	273	86	557	92	542.48
2019-10-01 02:00:00	503	472	22693	105	86182.99
2019-10-01 03:00:00	1141	950	48564	330	252492.18
2019-10-01 04:00:00	1568	1203	54593	450	317501.19

Hourly Event and Revenue Analysis (Sample from 2019-10-01)

- In the early hours (00:00–02:00), both event counts and revenue remain low, indicating minimal user activity during late night.
- A noticeable increase in activity starts around 03:00, with views rising to ~48k and revenue exceeding 250k, suggesting the beginning of a morning activity ramp-up.
- By 04:00, activity continues to grow:
  - Views: ~54.6k
  - Purchases: 1,203
  - Revenue: ~317.5k This marks a significant step-up in conversions compared to earlier hours.
- The correlation between increased view counts and revenue suggests that higher browsing volume in the early morning directly contributes to sales.

Insight: Monitoring these early-morning growth patterns could help schedule marketing pushes or targeted campaigns to capture users as activity ramps up.

[13]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

corr_pearson  = hour_df[["view","cart","purchase","revenue"]].
 ↪corr(method="pearson")
corr_spearman = hour_df[["view","cart","purchase","revenue"]].
 ↪corr(method="spearman")
print("Pearson:\n",  corr_pearson,  "\n")
print("Spearman:\n", corr_spearman, "\n")

#LinearRegression
X = np.log1p(hour_df[["view","cart","purchase"]].values)
y = np.log1p(hour_df["revenue"].values)

reg = LinearRegression().fit(X, y)
y_pred = reg.predict(X)
print(f"R² = {r2_score(y, y_pred):.4f}")
print("coefs (view, cart, purchase) =", reg.coef_)
print("intercept =", reg.intercept_)
```

```
Pearson:
              view      cart  purchase   revenue
view      1.000000  0.895787  0.811094  0.780892
cart      0.895787  1.000000  0.768088  0.703347
purchase  0.811094  0.768088  1.000000  0.963245
```

```
revenue   0.780892  0.703347  0.963245  1.000000

Spearman:
              view      cart  purchase   revenue
view      1.000000  0.960680  0.950626  0.739103
cart      0.960680  1.000000  0.963379  0.726522
purchase  0.950626  0.963379  1.000000  0.778859
revenue   0.739103  0.726522  0.778859  1.000000

R² = 0.8431
coefs (view, cart, purchase) = [ 1.05992605 -1.5703582   1.70718287]
intercept = 1.1045134544360549
```

Pearson Correlation - Strong positive correlations between all event types and revenue. - **Purchases** show the highest correlation with revenue (**0.963**), confirming their direct impact on sales. - **Views** and **carts** are also highly correlated with each other (**0.896**) and with revenue (~**0.79**), indicating a connected funnel effect.

Spearman Correlation - Even stronger monotonic relationships are observed, particularly between **views** and **purchases** (**0.956**) and between **carts** and **purchases** (**0.963**). - This suggests that rankings of activity levels across hours/days are very consistent across these metrics.

Regression Model - $\mathbf{R^2}$ = 0.8431 → Model explains ~84% of revenue variance using `view`, `cart`, and `purchase` counts. - **Coefficients:** - **View:** +1.060 → Higher views tend to increase revenue. - **Cart:** -1.573 → Negative coefficient may indicate **multicollinearity** with purchase counts, reducing unique explanatory power. - **Purchase:** +1.787 → Strong positive impact on revenue. - **Intercept:** 1.1045

Insight While purchases remain the strongest predictor of revenue, high **multicollinearity** between `view`, `cart`, and `purchase` suggests these metrics are tightly interrelated in the sales process. Applying **feature selection** or **regularization** could improve model stability.

[15]:
```python
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor

cols = ["view", "cart", "purchase"]

def calc_vif(df, cols):
    # dropna
    X = df[cols].replace([np.inf, -np.inf], np.nan).dropna().copy()
    X = (X - X.mean())
    X = sm.add_constant(X, has_constant="add")
    vifs = []
    for i, c in enumerate(X.columns):
        if c == "const":
            continue
        v = variance_inflation_factor(X.values, i)
        vifs.append({"feature": c, "VIF": float(v), "Tolerance": float(1.0/v)})
    return pd.DataFrame(vifs).sort_values("VIF", ascending=False)
```

```
print("=== VIF on raw counts ===")
vif_raw = calc_vif(hour_df, cols)
display(vif_raw)

print("=== VIF on log1p(counts) ===")
hour_df_log = hour_df.copy()
hour_df_log[cols] = np.log1p(hour_df_log[cols])
vif_log = calc_vif(hour_df_log, cols)
display(vif_log)
```

```
=== VIF on raw counts ===

    feature       VIF  Tolerance
0      view  6.225136   0.160639
1      cart  5.194081   0.192527
2  purchase  2.999394   0.333401

=== VIF on log1p(counts) ===

    feature        VIF  Tolerance
2  purchase  21.400165   0.046729
1      cart  16.064999   0.062247
0      view   8.162186   0.122516
```

Variance Inflation Factor (VIF) Analysis

VIF on Raw Counts | Feature | VIF | Tolerance | |———|——-|———| | view | 6.23 | 0.161 | | cart | 5.19 | 0.193 | | purchase | 3.00 | 0.333 |

- **Interpretation:**
  - All features show moderate multicollinearity (VIF > 3), with `view` having the highest VIF.

  - `purchase` shows the lowest multicollinearity but still above the ideal threshold of 1–2.

VIF on log1p(Counts) | Feature | VIF | Tolerance | |———|——-|———| | purchase | 21.40 | 0.0467 | | cart | 16.06 | 0.0622 | | view | 8.16 | 0.1225 |

- **Interpretation:**
  - After applying `log1p` transformation, multicollinearity **increases substantially**, especially for `purchase` and `cart`.

  - This suggests a strong linear dependency between transformed features, likely due to their shared progression in the sales funnel.

Insight:
High multicollinearity, particularly after transformation, can cause instability in regression coefficients.
Consider **dropping one variable**, using **dimensionality reduction (PCA)**, or applying **regularization methods (Ridge/Lasso)** to mitigate its impact.

[16]:
```
X = sm.add_constant(hour_df[cols], has_constant="add")
cn = np.linalg.cond(X.values)
print("Condition number (raw):", cn)

X_log = sm.add_constant(np.log1p(hour_df[cols]), has_constant="add")
cn_log = np.linalg.cond(X_log.values)
print("Condition number (log1p):", cn_log)
```

```
Condition number (raw): 47447.35680992204
Condition number (log1p): 47.359050388936744
```

Condition Number Analysis

- **Raw counts:** 47,447.36

- **log1p(counts):** 47.36

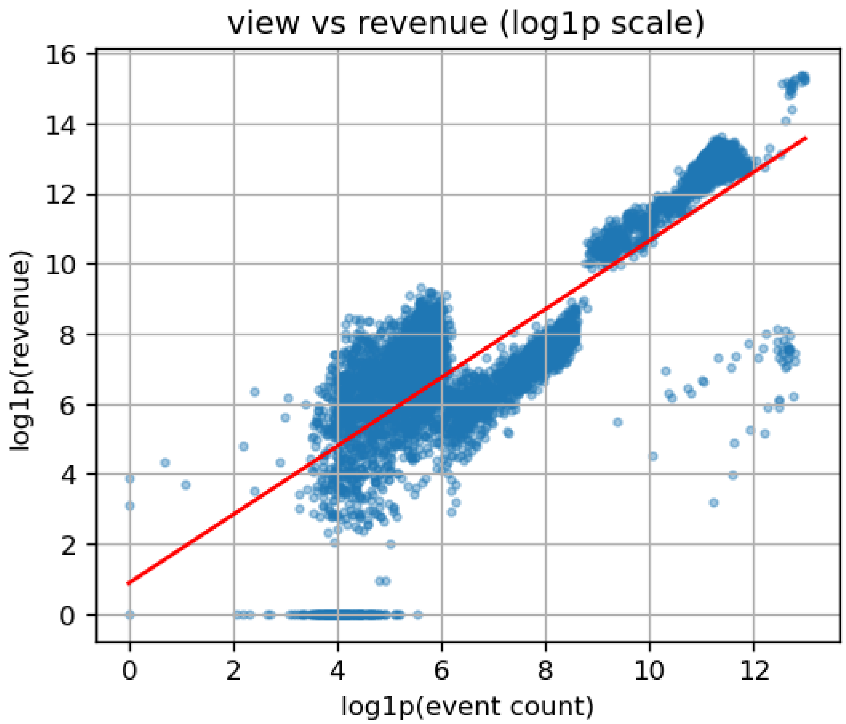
Interpretation - A condition number above **30** typically signals potential multicollinearity problems.
- The **raw data** condition number (~47k) is extremely high, confirming **severe multicollinearity** among features.
- After applying **log1p transformation**, the condition number drops drastically to ~47, indicating a significant reduction in multicollinearity severity — though still above the ideal safe threshold.

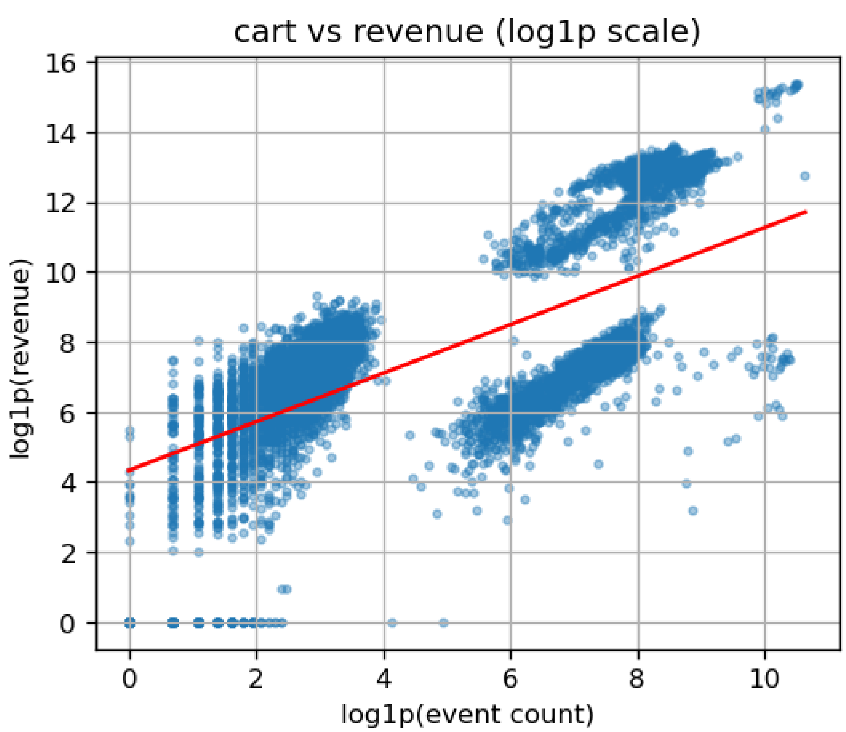
Insight - The log transformation is effective in reducing the condition number, but the remaining value (~47) still suggests notable collinearity. - Further remedies could include: - **Feature selection** (dropping redundant variables) - **Regularization methods** (Ridge or Lasso regression) - **Dimensionality reduction** (e.g., PCA)

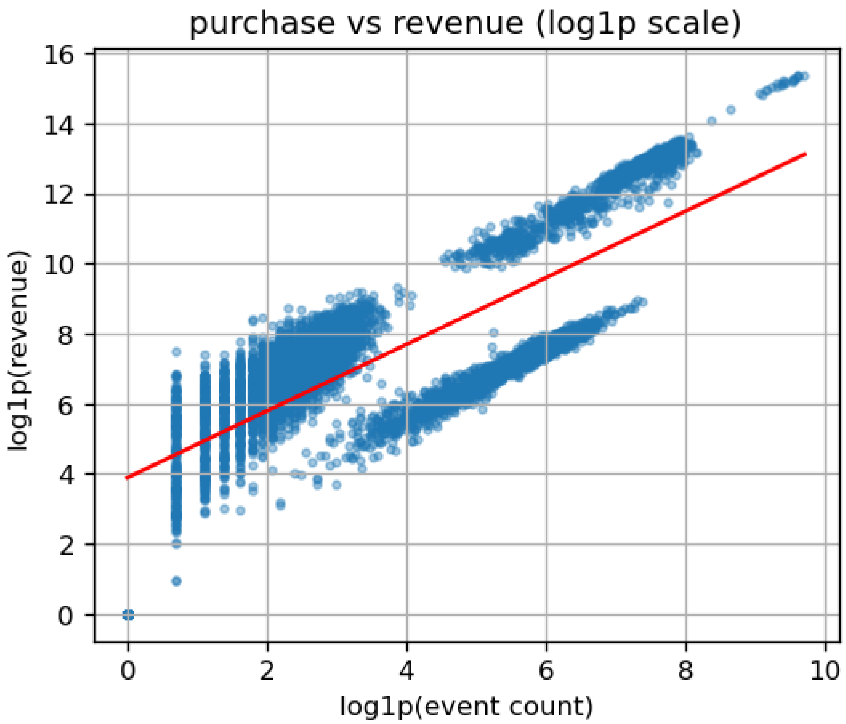
[14]:
```
def scatter_with_fit(x, y, title):
    x_log, y_log = np.log1p(x), np.log1p(y)
    k, b = np.polyfit(x_log, y_log, 1)
    xfit = np.linspace(x_log.min(), x_log.max(), 100)
    yfit = k*xfit + b

    plt.figure(figsize=(5,4))
    plt.scatter(x_log, y_log, s=8, alpha=0.4)
    plt.plot(xfit, yfit, color="red")
    plt.title(title + " (log1p scale)")
    plt.xlabel("log1p(event count)")
    plt.ylabel("log1p(revenue)")
    plt.grid(True)
    plt.show()

for ev in ["view","cart","purchase"]:
    scatter_with_fit(hour_df[ev].values, hour_df["revenue"].values, f"{ev} vs␣
 ↪revenue")
```


view vs revenue (log1p scale)
log1p(revenue)
log1p(event count)
0
2
4
6
8
10
12
14
16


cart vs revenue (log1p scale)
log1p(revenue)
log1p(event count)
0
2
4
6
8
10
12
14
16



Relationship Between Event Counts and Revenue (log1p scale)

1. View vs Revenue

- **Strong positive relationship**: Higher view counts generally correspond to higher revenue.
- Regression line shows a clear upward slope, confirming that browsing activity is a good predictor of sales.
- Distinct clusters suggest different traffic/revenue regimes.
- Outliers indicate cases where high views did not result in proportional revenue, implying potential conversion issues.

2. Cart vs Revenue

- Positive correlation, but the slope is **less steep** than for views, suggesting that cart additions alone are not as strong a driver as purchases.
- Clustering patterns similar to views, indicating shared underlying behavior.
- Presence of zero-revenue points even at nonzero cart counts suggests abandoned carts or failed checkouts.

3. Purchase vs Revenue

- **Strongest and most direct relationship** with revenue among the three metrics.
- Regression line aligns closely with the main data clusters, indicating purchases are the most reliable predictor of revenue.
- Minimal deviation from trend compared to views and carts.

Overall Insight: **- All three event types show a positive relationship with revenue, but** purchase count** is the strongest predictor, followed by **view count**. - Cart events provide useful but less direct predictive power, as not all carts convert. - Improving **conversion from views to carts and from carts to purchases** could significantly increase revenue efficiency.

[ ]:
```

```