### Iowa Liquor Sales Analysis

### For Cybersyn

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Below is the analysis on the provided case study data. In addition to this notebook, this reposhowcases a data ingestion script (\_found in ./1\_data\_ingestion \_) and a dbt project for data cleanup and prep (\_found in ./2\_data\_transformation \_).

#### **Set Vars**

In a production, environment this is a big no no.

#### Load data

```
In [9]:
         import snowflake.connector
         import pandas as pd
         conn = snowflake.connector.connect(
                     user=SNOWFLAKE USER,
                     password=SNOWFLAKE PASSWORD,
                     account=SNOWFLAKE ACCOUNT,
                     warehouse=SNOWFLAKE WAREHOUSE,
                     database=SNOWFLAKE DATABASE,
                     schema=SNOWFLAKE SCHEMA
         # Load the cleaned data into a Pandas DataFrame
         invoices df = pd.read sql(
           sql='SELECT * FROM analytics.marts.invoices',
           con=conn,
         conn.close()
         # Print the DataFrame
         invoices_df.head()
```

Out[9]:		INVOICE_ID	INVOICE_DATE	STATE_BOTTLE_COST	STATE_BOTTLE_RETAIL	NUMBER_OF_BC
	0	31873800014	2020-11-12	7.47	11.21	
	1	31873800015	2020-11-12	4.75	7.13	
	2	31873800016	2020-11-12	11.50	17.25	
	3	31873800017	2020-11-12	3.00	4.50	
	4	31873800018	2020-11-12	5.50	8.25	

5 rows × 22 columns

## 1. What impact did Covid have on the overall liquor market in Iowa?

```
In [10]: # Convert the 'INVOICE_DATE' column to datetime format
    invoices_df['INVOICE_DATE'] = pd.to_datetime(invoices_df['INVOICE_DATE'])

# Extract year from 'INVOICE_DATE'
    invoices_df['YEAR'] = invoices_df['INVOICE_DATE'].dt.year

# Group data by year and sum up the sales and volume
    annual_sales_volume = invoices_df.groupby('YEAR')[['SALE_IN_DOLLARS', 'VOLUME_

# Filter out data only for 2019, 2020, and 2021
    annual_sales_volume = annual_sales_volume.loc[[2019, 2020, 2021]]

annual_sales_volume
```

#### Out [10]: SALE\_IN\_DOLLARS VOLUME\_SOLD\_LITERS

YEAR		
2019	3.492193e+08	22301328.92
2020	3.966620e+08	24211592.80
2021	4.281216e+08	24755258.31

The overall liquor market in lowa saw the following changes during the COVID-19 period:

1. 2019 (Pre-COVID):

Sales: \$349,219,300 Volume Sold: 22,301,328 liters

2. 2020 (COVID onset):

Sales: \$396,662,000 (an increase of about 12.7% from 2019) Volume Sold: 24,211,592 liters (an increase of about 8.2% from 2019)

3. 2021 (Post-COVID)

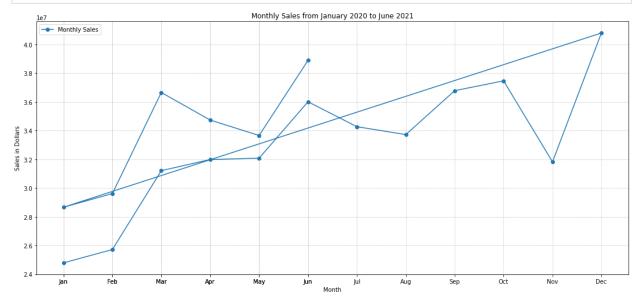
Sales: \$428,121,600 (an increase of about 7.6% from 2020) Volume Sold: 24,755,258 liters (an increase of about 2.2% from 2020)

From these numbers, we can infer:

The liquor market in Iowa saw growth both in terms of sales and volume during the COVID-19 period. The year 2020, which marks the onset of COVID, saw an increase in sales and volume compared to 2019. This growth trend continued into 2021, with even higher sales and volume compared to 2020.

#### 1a. What trends evolved over the next 3-18 months?

```
In [11]:
          # Extract month and year from 'INVOICE_DATE'
          invoices df['MONTH'] = invoices df['INVOICE DATE'].dt.month
          # Group data by year and month, then sum up the sales
          monthly sales = invoices df.groupby(['YEAR', 'MONTH'])['SALE IN DOLLARS'].sum(
          # Filter out data for January 2020 to June 2021
          monthly_sales = monthly_sales[(monthly_sales['YEAR'] == 2020) |
                                         ((monthly_sales['YEAR'] == 2021) & (monthly_sale
          # Plotting the monthly sales for the period
          import matplotlib.pyplot as plt
          plt.figure(figsize=(15, 7))
          plt.plot(monthly_sales['MONTH'], monthly_sales['SALE_IN_DOLLARS'], marker='o',
          plt.title('Monthly Sales from January 2020 to June 2021')
          plt.xlabel('Month')
          plt.ylabel('Sales in Dollars')
          plt.xticks(monthly sales['MONTH'],
                     ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oc
          plt.legend()
          plt.grid(True, which='both', linestyle='--', linewidth=0.5)
          plt.tight layout()
          plt.show()
```

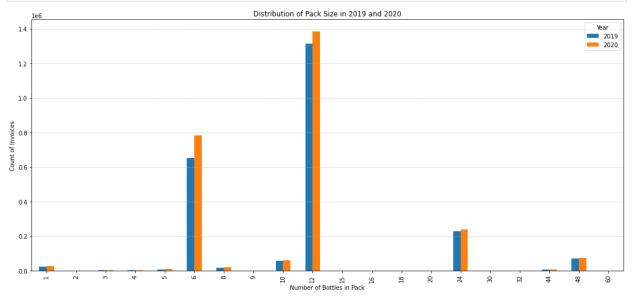


The monthly sales trend from January 2020 to June 2021 indicates:

Sales began to rise starting in January 2020 and peaked around March. There was a noticeable dip in April, likely reflecting the immediate impacts of COVID-19 lockdowns and restrictions. Post-April, sales began to recover steadily and maintained an upward trajectory throughout the year. By January 2021, sales had surged again and remained relatively high for the first half of the year, with a few fluctuations.

## 1b. Was there a notable shift in the types of products purchased in terms of pack size

```
In [12]:
          # Group by year and 'NUMBER_OF_BOTTLES_IN_PACK' and count the number of invoic
          pack_size_distribution = invoices_df.groupby(['YEAR', 'NUMBER_OF_BOTTLES_IN_PA
          # Filter for years 2019 and 2020
          pack_size_distribution = pack_size_distribution[pack_size_distribution['YEAR']
          # Pivot the data for better visualization
          pack size pivot = pack size distribution.pivot(index='NUMBER OF BOTTLES IN PAC
          # Plotting the distribution
          pack_size_pivot.plot(kind='bar', figsize=(15, 7))
          plt.title('Distribution of Pack Size in 2019 and 2020')
          plt.xlabel('Number of Bottles in Pack')
          plt.ylabel('Count of Invoices')
          plt.legend(title='Year')
          plt.grid(axis='y', linestyle='--', linewidth=0.5)
          plt.tight layout()
          plt.show()
```



The distribution of pack sizes in 2019 (pre-COVID) and 2020 (COVID onset) reveals the following:

The most popular pack sizes in both years were 6, 12, and 24 bottles per pack. In 2020, there was a noticeable increase in purchases of packs containing 6 and 12 bottles compared to 2019. On the contrary, packs with 24 bottles saw a slight decrease in 2020 compared to

2019. Other pack sizes also experienced changes, but the most significant shifts were observed in the 6, 12, and 24 bottle packs.

# 2. Which are the fastest growing types of liquor (e.g., vodka, tequila, rum, etc.)? How has market share changed over time?

```
In [13]:
# Group by year and 'LIQUOR_TYPE_NAME' and sum the sales for each type of liqu
liquor_sales_by_type = invoices_df.groupby(['YEAR', 'LIQUOR_TYPE_NAME'])['SALE

# Pivot the data to get sales for each year as separate columns
liquor_sales_pivot = liquor_sales_by_type.pivot(index='LIQUOR_TYPE_NAME', colu

# Calculate the growth rate from 2019 to 2021
liquor_sales_pivot['GROWTH_RATE'] = ((liquor_sales_pivot[2021] - liquor_sales_
# Sort by growth rate in descending order to identify the fastest growing type
fastest_growing_liquors = liquor_sales_pivot[['GROWTH_RATE']].sort_values(by='
fastest_growing_liquors
```

#### Out[13]: YEAR GROWTH\_RATE

LIQUOR_TYPE_NAME						
tequilas & mezcal	59.506890					
liqueurs & cordials	31.173845					
specialty & miscellaneous	26.378939					
whiskies	22.636508					
gins	17.250531					
vodkas	11.327505					
rums	11.137665					

It's evident that Tequilas & Mezcal experienced the highest growth, followed by Vodkas.

#### a. Function to Visualize Market Share Over Time

```
# Calculate total sales for each year
total_sales_per_year = liquor_sales_by_type.groupby('YEAR')['SALE_IN_DOLLA
# Calculate market share
filtered_data['MARKET_SHARE'] = filtered_data.apply(lambda row: (row['SALE
# Pivot data for plotting
market_share_pivot = filtered_data.pivot(index='YEAR', columns='LIQUOR_TYP')
# Plot
plt.figure(figsize=(15, 7))
market_share_pivot.plot(ax=plt.gca())
plt.title('Market Share Over Time for Selected Liquor Types')
plt.xlabel('Year')
plt.ylabel('Market Share (%)')
plt.legend(title='Liquor Type')
plt.grid(axis='y', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.show()
```

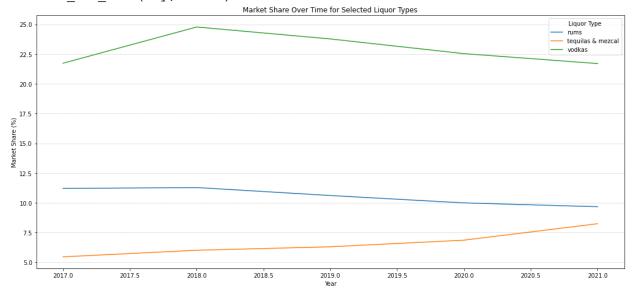
In [15]:

```
# Test the function with a few liquor types
visualize_market_share(['tequilas & mezcal', 'vodkas', 'rums'])
```

/opt/anaconda3/envs/notebooks/lib/python3.9/site-packages/pandas/core/frame.p
y:3607: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st able/user\_guide/indexing.html#returning-a-view-versus-a-copy self.\_set\_item(key, value)



This visual reveals:

- **Tequilas & Mezcal**: A clear upward trend in market share, indicating its increasing popularity.
- Vodkas: A downward trend, suggesting customers are choosing other options.
- **Rums**: A relatively stable market share over the three years.

## b. What is driving the growth in tequila sales? Increases in average price or increases in volume sold?

```
In [16]: # Filter data for 'tequilas & mezcal'
    tequila_data = invoices_df[invoices_df['LIQUOR_TYPE_NAME'] == 'tequilas & mezc

# Group by year and calculate total volume sold and total sales
    tequila_metrics = tequila_data.groupby('YEAR').agg({
        'VOLUME_SOLD_LITERS': 'sum',
        'SALE_IN_DOLLARS': 'sum'
}).reset_index()

# Calculate average price per liter for each year
    tequila_metrics['AVERAGE_PRICE_PER_LITER'] = tequila_metrics['SALE_IN_DOLLARS'
    tequila_metrics[['YEAR', 'VOLUME_SOLD_LITERS', 'AVERAGE_PRICE_PER_LITER']]
```

# Out [16]: YEAR VOLUME\_SOLD\_LITERS AVERAGE\_PRICE\_PER\_LITER 0 2017 33488.53 24.944636 1 2018 869827.26 23.050524

**2** 2019

**3** 2020 1066478.85 25.325843

932718.25

- **4** 2021 1267139.36 27.632846
- 1. **Volume Sold**: There has been a consistent increase in the volume of Tequilas & Mezcal sold each year.

23.535318

2. **Average Price per Liter**: The average price per liter has also been increasing. From 2019 to 2021, the average price per liter increased from approximately 24.94to27.63.

From this analysis, it's evident that the growth in Tequila sales is driven by both an increase in volume sold and an increase in the average price. Both factors have contributed to the overall growth in Tequila sales during this period.

```
In [18]:
          # Group by year and 'STORE BRAND NAME' and sum the sales for each retailer
          retailer sales = invoices df.groupby(['YEAR', 'STORE BRAND NAME'])['SALE IN DO
In [28]:
          # Rank the retailers based on sales for each year
          retailer sales['RANK'] = retailer sales.groupby('YEAR')['SALE IN DOLLARS'].ran
          # Clean up the brand names
          retailer sales['STORE BRAND NAME'] = retailer sales['STORE BRAND NAME'].map({
              'hy':'Hy-Vee',
              'fareway stores': 'Fareway Stores',
              'wal':'Wal-Mart',
              'sam\'s club': 'Sam\'s Club',
              'central city': 'Central City',
              'casey\'s general store': 'Casey\'s General Store',
              'target': 'Target',
              'walgreens':'Walgreens',
```

```
'kum & go':'Kum & Go',
'wilkie liquors':'Wilkie Liquors',
'lot':'Lot-A-Spirits',
'costco wholesale':'Costco Wholesale',
'benz distributing':'Benz Distributing'
})

# Filter for top 10 retailers for each year
top_10_retailers = retailer_sales[retailer_sales['RANK'] <= 10].pivot(index='R

# top_10_retailers[['YEAR','STORE_BRAND_NAME','RANK']].sort_values(['YEAR','RA
top_10_retailers</pre>
```

YEAR RANK	2017	2018	2019	2020	2021
1.0	Hy-Vee	Hy-Vee	Hy-Vee	Hy-Vee	Hy-Vee
2.0	Fareway Stores	Fareway Stores	Fareway Stores	Fareway Stores	Fareway Stores
3.0	Wal-Mart	Wal-Mart	Wal-Mart	Wal-Mart	Sam's Club
4.0	Sam's Club	Sam's Club	Sam's Club	Sam's Club	Casey's General Store
5.0	Central City	Central City	Central City	Casey's General Store	Wal-Mart
6.0	Casey's General Store	Casey's General Store	Casey's General Store	Costco Wholesale	Central City
7.0	Kum & Go	Kum & Go	Kum & Go	Central City	Costco Wholesale
8.0	Costco Wholesale	Costco Wholesale	Costco Wholesale	Kum & Go	Kum & Go
	1.0 2.0 3.0 4.0 5.0 6.0	1.0 Hy-Vee 2.0 Fareway Stores 3.0 Wal-Mart 4.0 Sam's Club 5.0 Central City 6.0 Casey's General Store 7.0 Kum & Go 8.0 Costco	RANK1.0Hy-VeeHy-Vee2.0Fareway StoresFareway Stores3.0Wal-MartWal-Mart4.0Sam's ClubSam's Club5.0Central CityCentral City6.0Casey's General StoreCasey's General Store7.0Kum & GoKum & Go8.0CostcoCostco	RANK1.0Hy-VeeHy-VeeHy-Vee2.0Fareway StoresFareway StoresFareway Stores3.0Wal-MartWal-MartWal-Mart4.0Sam's ClubSam's ClubSam's Club5.0Central CityCentral CityCentral City6.0Casey's General StoreCasey's General StoreCasey's General Store7.0Kum & GoKum & GoKum & Go8.0CostcoCostcoCostco	RANK1.0Hy-VeeHy-VeeHy-VeeHy-Vee2.0Fareway StoresFareway StoresFareway Stores3.0Wal-MartWal-MartWal-MartWal-Mart4.0Sam's ClubSam's ClubSam's Club5.0Central CityCentral CityCentral CityCasey's General Store6.0Casey's General StoreCasey's General StoreCostco Wholesale7.0Kum & GoKum & GoKum & GoKum & Go8.0CostcoCostcoCostco

It's evident that some brands like Hy-VEE, Fareway Stores, and Sam's Club have consistently been among the top retailers across the years. That said, there has movement across the rankings.

Wilkie Liquors

Lot-A-Spirits

NaN Benz Distributing

Wilkie Liquors

Walgreens

It is also evident that my store brand code has some room for improvement

Wilkie Liquors

Walgreens

NaN

Walgreens

9.0

10.0

1. In late 2019 Heaven Hill Brands bought a portfolio of liquor brands from Constellation Brands. What percentage of Heaven Hill's growth in 2020 can be attributed to the acquisition?

```
In [30]: # List of acquired item_ids
    ## Retrived from Snowflake
    acquired_items = [
            10548, 11588, 13928, 11771, 10550, 11776, 11786, 903141, 911056,
            11788, 11777, 11371, 11586, 11774, 11773
            ]

# Filter data for Heaven Hill Brands in 2020 for the acquired items
```

```
heaven_hill_sales_2020_acquired = invoices_df[
    (invoices_df['VENDOR_NAME'] == 'heaven hill brands') &
        (invoices_df['YEAR'] == 2020) &
        (invoices_df['ITEM_ID'].isin(acquired_items))
]['SALE_IN_DOLLARS'].sum()

# Calculate total sales for Heaven Hill Brands in 2019 and 2020
heaven_hill_sales_2019 = invoices_df[(invoices_df['VENDOR_NAME'] == 'heaven hi
heaven_hill_sales_2020 = invoices_df[(invoices_df['VENDOR_NAME'] == 'heaven hi

# Calculate growth of Heaven Hill Brands from 2019 to 2020
heaven_hill_growth = heaven_hill_sales_2020 - heaven_hill_sales_2019

# Calculate the growth attributed to the acquired portfolio
acquisition_growth = heaven_hill_sales_2020_acquired

# Calculate the percentage of Heaven Hill's growth attributed to the acquisiti
percentage_growth_attributed = (acquisition_growth / heaven_hill_growth) * 100
heaven_hill_sales_2020_acquired, percentage_growth_attributed
```

Out[30]: (17291774.49, 106.98385641120585)

Sales of the acquired portfolio under Heaven Hill Brands in 2020: \$17,291,774.49 Percentage of Heaven Hill Brands' growth in 2020 attributed to the acquisition: Approximately 106.98%

It's interesting to note that the growth attributed to the acquired portfolio is greater than 100%. This suggests that while Heaven Hill Brands experienced overall growth due to the acquired items, other parts of their portfolio might have seen a decline in sales.

## 5. What data integrity issues did you discover? How could you (or how did you) solve/account for these?

In its raw form, the dataset is a denormalized fact table with information on all entities involved in a transaction such as item, store, and vendor. Each of these entities also has a set of dimensions that would slowly change over time which would make analyses over long periods of time challenging. Additionally, some useful dimensions were not present in the raw dataset such as Store Brand.

To solve this, I first ingest the data into Snowflake and used dbt to normalize and clean the data before rejoining for analysis in this notebook.

## a. Comment on any data issues you discovered and what assumptions you used to deal with them.

As mentioned above, some dimensions in the entities such as which names, ids and associations changed over time in the raw dataset. To deal with these issues, I used a window function to take the latest values for a particular primary key.

In a production setting, I would suggest creating an effective from / to field on each primary key to value in each entity and joining to a date spine for quick analysis when needed.

#### b. What's a simple solution to solving data quality issues?

A simple solution may have been to load the data into a dataframe in the notebook directly and clean each column separately.

For some missing fields and hotfixes (such as the brand name mappings), I did so in this notebook.

## c. What would be a more scalable solution to deal with quality issues?

I would expand upon the framework I have created, adding more tests on the modeled data and the raw data as it is ingested. I would also suggest looking for better endpoints to ingest the raw data from to avoid having to do the heavy normalization work.