# **Recipes Research Project**

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**Website Link**: <a href="https://jiangqiw.github.io/Recipes-Research-Project/">https://jiangqiw.github.io/Recipes-Research-Project/</a>)

```
In [1]: import plotly io as pio pio. renderers. default='notebook'
```

#### Code

#### Introduction

The world of cooking and food has grown exponentially over the years, with a vast array of recipes and cuisines available at our fingertips. In this project, we aim to dive into an extensive dataset consisting of recipes and their respective ratings. Our goal is to uncover trends and patterns that can provide valuable insights into the factors contributing to the popularity and success of a recipe.

The dataset is sourced from food.com and contains recipes and reviews posted since 2008. The data is divided into two parts: recipes and ratings. The recipes dataset includes information such as recipe name, ID, preparation time, contributor ID, submission date, tags, nutrition information, number of steps, steps text, and description. The ratings dataset, on the other hand, contains user ID, recipe ID, date of interaction, rating, and review text.

In the project, we will be first cleaning the data set and conduct exploratory data analysis, to obtain some basic information of the data set and relation between columns. Then, we will assess the missingness contained in the data set by NMAR analysis and analyzing the missingness dependency. Last, we would focus on the research question that, are complex recipes and simple recipes rated in the same scale. We would define recipe with fewer than 10 steps as simple recipes, and with more than 10 steps as complex recipes. We would analyze the rating scale related to the complexity of the recipe.

# Import required package and import the data set from csv file

```
In [2]: import pandas as pd
   import numpy as np
   import os
   from scipy.stats import ks_2samp
   import plotly.express as px
   import plotly.figure_factory as ff
   pd.options.plotting.backend = 'plotly'
```

In [3]: recipes = pd.read\_csv(os.path.join('food\_data', 'RAW\_recipes.csv'))
recipes.head()

#### Out[3]:

	name	id	minutes	contributor_id	submitted	tags	nutrition	n_steps	steps
0	brownies in the world best ever	333281	40	985201	2008-10- 27	['60- minutes- or-less', 'time-to- make', 'course	[138.4, 10.0, 50.0, 3.0, 3.0, 19.0, 6.0]	10	['heat t oven 350f a arran the ra
1	1 in canada chocolate chip cookies	453467	45	1848091	2011-04- 11	['60- minutes- or-less', 'time-to- make', 'cuisin	[595.1, 46.0, 211.0, 22.0, 13.0, 51.0, 26.0]	12	['pi he oven t 3 degre f', 'ir mix
2	412 broccoli casserole	306168	40	50969	2008-05- 30	['60- minutes- or-less', 'time-to- make', 'course	[194.8, 20.0, 6.0, 32.0, 22.0, 36.0, 3.0]	6	['prehe oven 3 degree 'spray 2 que
3	millionaire pound cake	286009	120	461724	2008-02- 12	['time-to- make', 'course', 'cuisine', 'prepara	[878.3, 63.0, 326.0, 13.0, 20.0, 123.0, 39.0]	7	['frehe the ov to 3 degree 'grease
4	2000 meatloaf	475785	90	2202916	2012-03- 06	['time-to- make', 'course', 'main- ingredient',	[267.0, 30.0, 12.0, 12.0, 29.0, 48.0, 2.0]	17	['pan baco and s aside a par tov
4									

```
In [4]: interaction = pd.read_csv(os.path.join('food_data', 'RAW_interactions.csv'))
interaction.head()
```

Out[4]:

review	rating	date	recipe_id	user_id	
So simple, so delicious! Great for chilly fall	5	2011-12-21	40893	1293707	0
I made the Mexican topping and took it to bunk	5	2010-02-27	85009	126440	1
Made the cheddar bacon topping, adding a sprin	5	2011-10-01	85009	57222	2
Just an observation, so I will not rate. I fo	0	2011-08-06	120345	124416	3
This recipe was OVERLY too sweet. I would sta	2	2015-05-10	120345	2000192946	4

## **Data cleaning**

First I check the data type for each column and think about the necessary data cleaning steps.

```
[5]:
        # checking data type
         recipes. dtypes
Out[5]: name
                            object
         id
                             int64
                             int64
         minutes
         contributor id
                             int64
         submitted
                            object
                            object
         tags
                            object
         nutrition
                             int64
         n_steps
         steps
                            object
         description
                            object
         ingredients
                            object
         n ingredients
                             int64
         dtype: object
```

The first step we are going to do to the dataframe is the tags, steps and ingredients columns. The three column all look like lists of string, but by checking the specific entry in the dataframe, we find that they are actually not lists. This could due to when web scraping, data collecter does not convert the text into list. As a result, we take action to convert the these three columns into list of string.

```
In [6]: # changing columns into list
    recipes['tags'] = recipes['tags'].str.strip('[').str.strip(']').str.split(',')
    recipes['steps'] = recipes['steps'].str.strip('[').str.strip(']').str.split(',')
    recipes['ingredients'] = recipes['ingredients'].str.strip('[').str.strip(']').str.split(',')
```

Then, since there are two dataframe but with common column, which are id and  $recipe\_id$ . As a result, we merge the two dataframe together to show the recipes and corresponding rating and review.

In [7]: # Merging two dataframe
merged = recipes.merge(interaction, left\_on='id', right\_on='recipe\_id', how = 'left')
merged.head()

Out[7]:

	name	id	minutes	contributor_id	submitted	tags	nutrition	n_steps	steps
0	brownies in the world best ever	333281	40	985201	2008-10- 27	['60-minutes- or-less', 'time-to- make', 'cour	[138.4, 10.0, 50.0, 3.0, 3.0, 19.0, 6.0]	10	['heat the oven to 350f and arrange the rack i
1	1 in canada chocolate chip cookies	453467	45	1848091	2011-04- 11	['60- minutes- or-less', 'time-to- make', 'cuis	[595.1, 46.0, 211.0, 22.0, 13.0, 51.0, 26.0]	12	['pre- heat oven the 350 degrees f', 'in a mix
2	412 broccoli casserole	306168	40	50969	2008-05- 30	['60- minutes- or-less', 'time-to- make', 'cour	[194.8, 20.0, 6.0, 32.0, 22.0, 36.0, 3.0]	6	['preheat oven to 350 degrees', 'spray a 2 qu
3	412 broccoli casserole	306168	40	50969	2008-05- 30	['60-minutes- or-less', 'time-to- make', 'cour	[194.8, 20.0, 6.0, 32.0, 22.0, 36.0, 3.0]	6	['preheat oven to 350 degrees', 'spray a 2 qu
4	412 broccoli casserole	306168	40	50969	2008-05- 30	['60-minutes- or-less', 'time-to- make', 'cour	[194.8, 20.0, 6.0, 32.0, 22.0, 36.0, 3.0]	6	['preheat oven to 350 degrees', 'spray a 2 qu
4									•

We find in the interaction dataframe, one important data is the rating for the recipes. As a result, we add new column name  $ave\_rating$ , which include the average rating for the column. Also, we believe that the 0 in the rating might be empty rating that people do not fill in. As a result, we replace 0 with nan value

```
In [8]: # Add average rating column and replace 0 with nan
    ser = merged.groupby('id').agg({'rating': 'mean'}).replace(0, np.nan)['rating']
    recipes = recipes.set_index('id')
    recipes['ave_rating'] = ser
    recipes = recipes.reset_index()
```

We also find that the <code>nutrition</code> column in the dataframe look like a list containing float but actually not. We find that in the list, the float represent: 'calories', 'total fat (PDV)', 'sugar (PDV)', 'sodium (PDV)', 'protein (PDV)', 'saturated fat (PDV)', 'carbohydrates (PDV)' . As a result, we first convert the column into list of float and create individual column for each nutrition

```
In [9]: # changing nutrition into column and create individual columns for each nutrition
    recipes['nutrition'] = recipes['nutrition'].str.strip('[').str.strip(']').str.split(',
    nutrient_names = ['calories', 'total fat (PDV)', 'sugar (PDV)', 'sodium (PDV)', 'prote
    for index, nutrient in enumerate(nutrient_names):
        recipes[nutrient] = recipes['nutrition'].apply(lambda x: x[index])
        recipes[nutrient] = pd.to_numeric(recipes[nutrient], errors='coerce')
```

```
In [10]: # Changing submitted column into datetime
  recipes['submitted'] = pd. to_datetime(recipes['submitted'])
```

In [11]: recipes. head()

### Out[11]:

	id	name	minutes	contributor_i	id submitted	tags	nutrition	n_steps	steps
0	333281	brownies in the world best ever	40	98520	2008-10- 27	['60- minutes-or- less', 'time- to-make', 'cour	[138.4, 10.0, 50.0, 3.0, 3.0, 19.0, 6.0]	10	['heat ove 350f arra the r
1	453467	1 in canada chocolate chip cookies	45	184809	2011-04- 11	['60- minutes-or- less', 'time- to-make', 'cuis	[595.1, 46.0, 211.0, 22.0, 13.0, 51.0, 2	12	['l t oven degr f', ' m
2	306168	412 broccoli casserole	40	5096	2008-05- 30	['60- minutes-or- less', 'time- to-make', 'cour	[194.8, 20.0, 6.0, 32.0, 22.0, 36.0, 3.0]	6	['prel' ove degre 'spra 2 c
3	286009	millionaire pound cake	120	46172	2008-02- 12	['time-to- make', 'course', 'cuisine', 'prep	[878.3, 63.0, 326.0, 13.0, 20.0, 123.0,	7	['freh the o to degre 'gre
4	475785	2000 meatloaf	90	220291	6 2012-03- 06	['time-to- make', 'course', 'main- ingredient'	[267.0, 30.0, 12.0, 12.0, 29.0, 48.0, 2.0]	17	['par bac and aside a pa
4									•

```
[12]:
          recipes. dtypes
Out[12]: id
                                            int64
                                           object
           name
                                            int64
          minutes
                                            int64
           contributor_id
                                   datetime64[ns]
           submitted
           tags
                                           object
           nutrition
                                           object
                                            int64
           n_steps
                                           object
           steps
           description
                                           object
                                           object
           ingredients
           n\_ingredients
                                            int64
                                          float64
           ave_rating
           calories
                                          float64
                                          float64
           total fat (PDV)
           sugar (PDV)
                                          float64
           sodium (PDV)
                                          float64
           protein (PDV)
                                          float64
           saturated fat (PDV)
                                          float64
           carbohydrates (PDV)
                                          float64
           dtype: object
In [13]:
          df display = recipes.drop(['description'], axis = 1)
           #print(df display.head(3).to markdown(index=False))
```

#### **EDA**

Frist we would analyze the distribution of number of ingredients

```
In [14]: df = recipes.groupby('n_ingredients').count().reset_index()
    fig1 = px.bar(df, x = 'n_ingredients', y = 'name')
    fig1.update_yaxes(title='Count')
    fig1.update_layout(title='Distribution of Number of Ingredients')
```

## Distribution of Number of Ingredients

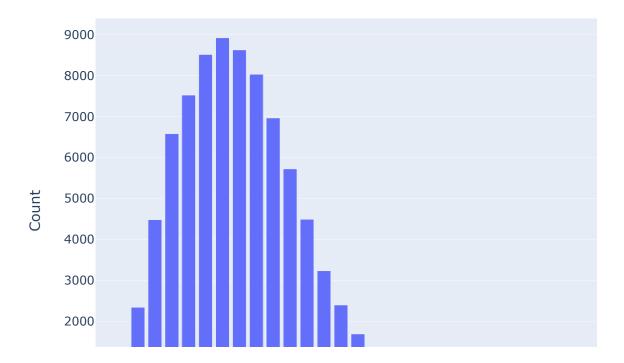
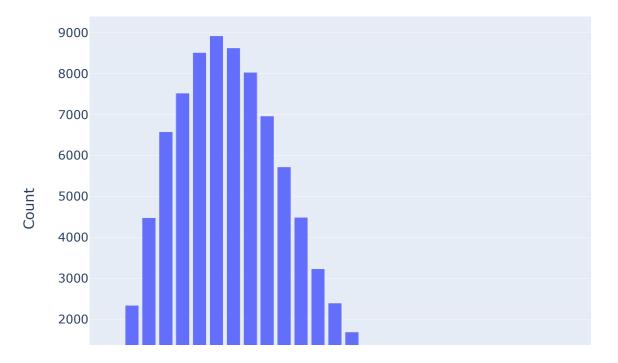


fig1. show('notebook')

## Distribution of Number of Ingredients

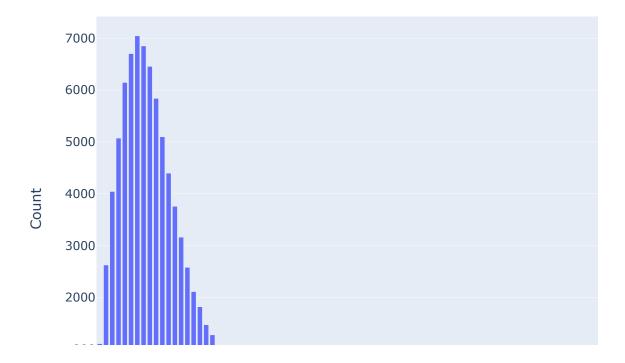


This shows that the distribution could be approximate as a gaussian distribution but skewed right. We would say that the graph centered around 8, meaning that most recipes have 8 ingredients.

Then we analyze the distribution of number of steps

```
In [16]: df1 = recipes.groupby('n_steps').count().reset_index()
    fig2 = px.bar(df1, x = 'n_steps', y = 'name')
    fig2.update_yaxes(title='Count')
    fig2.update_layout(title='Distribution of Number of Steps')
    fig2.show()
```

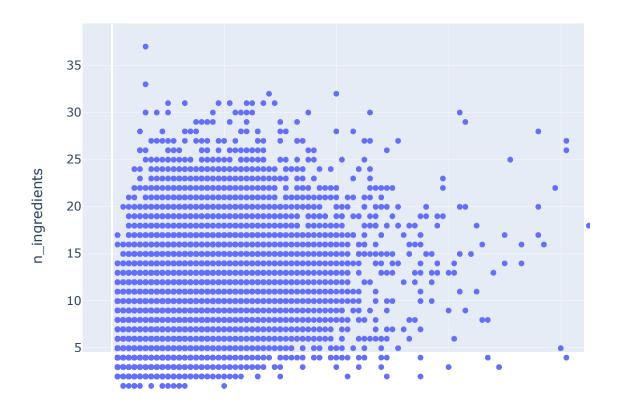
## Distribution of Number of Steps



The distrubution also show similar trend in the number of steps, which is a right skewed gaussian distribution. By comparing at the two graph, the graph for the number of distribution is more centered. The center for the graph is around 7, meaning most recipes have 7 steps. Also, we could see the graph have a lot outliers that have very big step numbers. After observing the dataset and also consider together with the minutes column and real life situation, we decided to choose steps greater than 40 and minutes greater than 200 as outlier and not faithful data

Then, we do bivariate analysis between the number of steps and the number of ingredients

```
In [17]: fig3 = px.scatter(recipes, x = 'n_steps', y = 'n_ingredients')
    fig3.show()
```



When the individual distribution for number of steps and number of ingredients seems very similar, the scatter plot does not know very strong correlation between the number of steps and number of ingredient. We could say that there is weak positive relationship between the number of steps and the number of ingredients.

Then, we draw line graph to present the relationship between number of ingredients and the average rating of recipe

```
In [18]: df2 = recipes.groupby('n_ingredients').mean().reset_index()
fig4 = px.line(df2, x = 'n_ingredients', y = 'ave_rating')
fig4.show()
```



We could see that the average rating and the number of ingredients in the recipes do not have much relationship with each other. Especially with number of ingredients smaller than 15, it is almost a horizontal line, showing no relationship between the two variables. The large fluctuate with number of ingredients larger than 15 could be due to relatively small data size collected within that range.

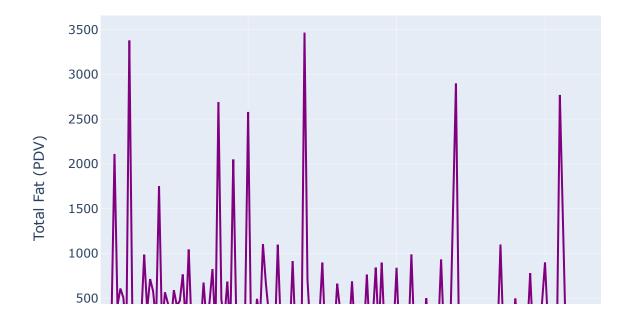
Interesting Aggregates: Analyzing the total fat with the cooking minutes

```
In [19]: import plotly.graph_objs as go
    recipes_df = recipes.copy()

recipes_df = recipes_df[recipes_df['minutes'] <= 200] # get rid of outliers
    pivot_table = recipes_df.pivot_table(values='total fat (PDV)', index='minutes', aggfu
    pivot_table = pivot_table.reset_index()
    fig6 = go.Figure()

fig6.add_trace(go.Scatter(x=pivot_table['minutes'], y=pivot_table[('mean', 'total fat
    fig6.add_trace(go.Scatter(x=pivot_table['minutes'], y=pivot_table[('min', 'total fat
    fig6.add_trace(go.Scatter(x=pivot_table['minutes'], y=pivot_table[('min', 'total fat
    fig6.add_trace(go.Scatter(x=pivot_table['minutes'], y=pivot_table[('max', 'total fat
    fig6.update_layout(title='Total Fat (PDV) by Cooking Time', xaxis_title='Cooking Time
    fig6.show()</pre>
```

#### Total Fat (PDV) by Cooking Time



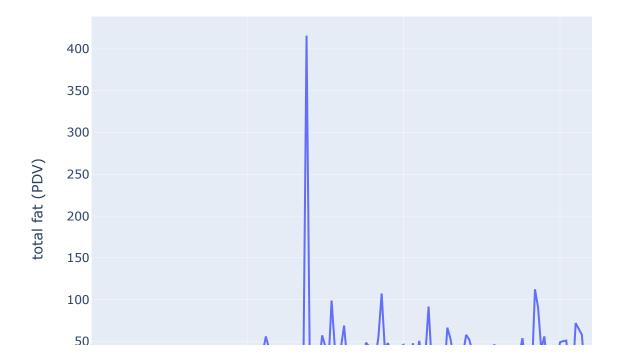
In [20]: pivot\_table

Out[20]:

	minutes	mean	median	min	max
		total fat (PDV)	total fat (PDV)	total fat (PDV)	total fat (PDV)
0	0	46.000000	46.0	46.0	46.0
1	1	7.786026	0.0	0.0	159.0
2	2	9.690529	0.0	0.0	419.0
3	3	12.579381	2.0	0.0	411.0
4	4	20.471910	7.0	0.0	258.0
182	192	36.333333	24.0	4.0	81.0
183	193	14.000000	14.0	14.0	14.0
184	195	37.130252	21.0	0.0	455.0
185	198	27.000000	27.0	27.0	27.0
186	200	41.764706	21.0	0.0	455.0

187 rows × 5 columns

```
In [21]: df4 = recipes_df.groupby('minutes').mean().reset_index()
    fig7 = px.line(df4, x = 'minutes', y = 'total fat (PDV)')
# Show the chart
    fig7.show()
```



One interesting result that we find in the aggregates data is that there is a peek for total fat in the recipe around 60 minutes of cooking time. Otherwise the recipes' total fat is fluctuate around 50 PDV, which is around 1000 calories. This shows that most recipes collected are recipes for health food.

#### **Assessment of Missingness**

```
[22]:
          ###### a lot of objects in columns
In
          merged_df = recipes.merge(interaction, left_on='id', right_on='recipe_id', how = 'lef
          merged df = merged df.drop('ave rating', axis = 1)
          ### missing description rating review
          merged df['rating'] = merged df['rating'].replace(0, np. nan)
          merged df.info()
          merged df. head()
          <class 'pandas.core.frame.DataFrame'>
          Int64Index: 234429 entries, 0 to 234428
          Data columns (total 24 columns):
           #
               Column
                                     Non-Null Count
                                                      Dtype
           0
               id
                                     234429 non-null
                                                      int64
           1
               name
                                     234428 non-null
                                                      object
           2
               minutes
                                     234429 non-nu11
                                                      int64
           3
                                     234429 non-null int64
               contributor id
           4
               submitted
                                     234429 non-null
                                                      datetime64[ns]
           5
               tags
                                     234429 non-null
                                                      object
           6
                                     234429 non-null
                                                      object
               nutrition
           7
                                     234429 non-null
               n steps
                                                      int64
           8
               steps
                                     234429 non-null
                                                     object
           9
                                     234315 non-null
               description
                                                      object
           10
               ingredients
                                     234429 non-null
                                                      object
               n ingredients
                                     234429 non-nu11
                                                      int64
           11
           12
               calories
                                     234429 non-null
                                                     float64
               total fat (PDV)
                                     234429 non-null float64
           13
           14
               sugar (PDV)
                                     234429 non-null float64
           15
               sodium (PDV)
                                     234429 non-null float64
                                     234429 non-null float64
           16
               protein (PDV)
                                     234429 non-null float64
           17
               saturated fat (PDV)
               carbohydrates (PDV)
                                     234429 non-null float64
           18
               user_id
           19
                                     234428 non-null float64
                                     234428 non-null float64
           20
               recipe id
           21
               date
                                     234428 non-null object
           22
               rating
                                     219393 non-null float64
           23
               review
                                     234371 non-null
                                                      object
```

memory usage: 44.7+ MB

dtypes: datetime64[ns](1), float64(10), int64(5), object(8)

#### Out[22]:

	id	name	minutes	contributor_id	submitted	tags	nutrition	n_steps	steps
0	333281	brownies in the world best ever	40	985201	2008-10- 27	['60- minutes- or-less', 'time-to- make', 'cour	[138.4, 10.0, 50.0, 3.0, 3.0, 19.0, 6.0]	10	['heat the oven to 350f and arrange the rack i
1	453467	1 in canada chocolate chip cookies	45	1848091	2011-04- 11	['60- minutes- or-less', 'time-to- make', 'cuis	[595.1, 46.0, 211.0, 22.0, 13.0, 51.0, 2	12	['pre- heat oven the 350 degrees f', 'in a mix
2	306168	412 broccoli casserole	40	50969	2008-05- 30	['60-minutes- or-less', 'time-to- make', 'cour	[194.8, 20.0, 6.0, 32.0, 22.0, 36.0, 3.0]	6	['preheat oven to 350 degrees', 'spray a 2 qu
3	306168	412 broccoli casserole	40	50969	2008-05- 30	['60-minutes- or-less', 'time-to- make', 'cour	[194.8, 20.0, 6.0, 32.0, 22.0, 36.0, 3.0]	6	['preheat oven to 350 degrees', 'spray a 2 qu
4	306168	412 broccoli casserole	40	50969	2008-05- 30	['60- minutes- or-less', 'time-to- make', 'cour	[194.8, 20.0, 6.0, 32.0, 22.0, 36.0, 3.0]	6	['preheat oven to 350 degrees', 'spray a 2 qu

#### 5 rows × 24 columns

```
→
```

```
In [23]: def create_kde_plotly(df, group_col, group1, group2, vals_col, title=''):
    fig = ff.create_distplot(
        hist_data=[df.loc[df[group_col] == group1, vals_col], df.loc[df[group_col] ==
        group_labels=[group1, group2],
        show_rug=False, show_hist=False,
        colors=['#ef553b', '#636efb'],
    )
    return fig.update_layout(title=title)
```

```
merged df. select dtypes (include=['int64', 'float64']). columns
Out[24]: Index(['id', 'minutes', 'contributor_id', 'n_steps', 'n_ingredients',
                  calories', 'total fat (PDV)', 'sugar (PDV)', 'sodium (PDV)'
                  'protein (PDV)', 'saturated fat (PDV)', 'carbohydrates (PDV)',
                  'user id', 'recipe id', 'rating'],
                 dtype='object')
In
   [25]:
          ### MAR and MCAR Dependency Testing
          ## n steps and rating dependency
          def dependency test (column name, num, merged df):
              merged_df = merged df.copy()
                 igr = merged df[column name].quantile(0.75) - merged df[column name].quantile(0.
          #
                 threshold = 1.5*iqr + merged df[column name].quantile(0.25)
                merged df = merged df.loc[merged df[column name] <= threshold, :]</pre>
              print(f'#######{column name}#######')
               true diff = abs(merged df.loc[merged df['rating'].isna(), column name].mean() - m
               simulate diff = []
              for k in range (1000):
                   merged df['shuffle rating'] = np. random. permutation(merged df['rating'])
                   temp diff = abs(merged df.loc[merged df['shuffle rating'].isna(), column name
                   simulate diff.append(temp diff)
              print((simulate diff >= true diff).mean())
              fig2 = px. histogram(pd. DataFrame(simulate diff), x=0, nbins=50, histnorm='probabi
                                  title='Empirical Distribution of the Absolute Difference in Mea
              fig2. add vline (x=true diff, line color='red')
              fig2.add annotation(text=f'<span style="color:red">Observed Absolute Difference in
                                  x=1.45 * true_diff, showarrow=False, y=0.07)
              ks test = ks 2samp(merged df.loc[merged df['rating'].isna(), column name], merged
              print(ks test.pvalue)
              merged df['missing rating'] = merged df['rating'].isna()
              fig = create kde plotly (merged df, 'missing rating', True, False, column name,
                                       f"Food {column name} by Missingness of Food Rating")
              fig. show()
              fig2. show()
              fig.write_html(f'fig{num}.html', include plotlyjs='cdn')
              fig2.write html(f'fig{num + 1}.html', include plotlyjs='cdn')
```

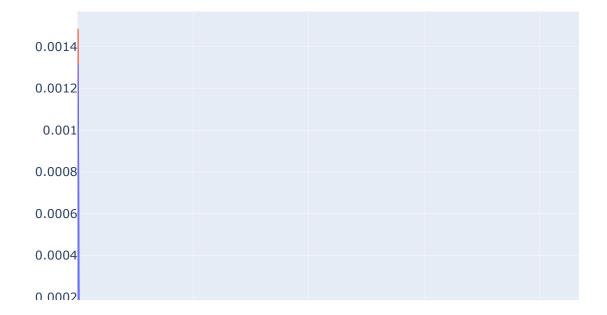
In [34]: dependency\_test('minutes', 11, merged\_df)

#######minutes#######

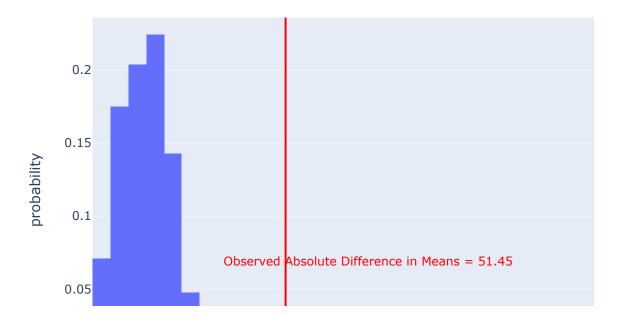
0.124

1. 4191797241819564e-107

## Food minutes by Missingness of Food Rating



# Empirical Distribution of the Absolute Difference in Means



In [27]: dependency\_test('calories', 13, merged\_df)

#######calories#######

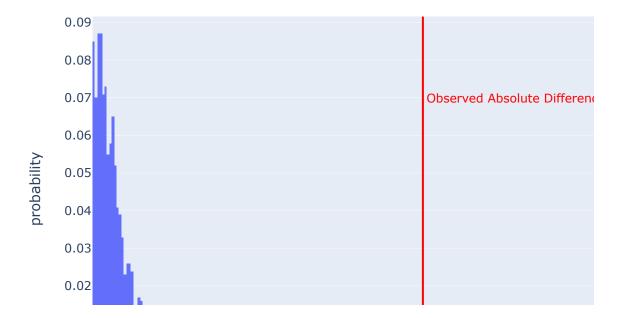
0.0

7. 960756339494917e-35

## Food calories by Missingness of Food Rating



# Empirical Distribution of the Absolute Difference in Means



# **Hypothesis Testing**

In	[28]:	recipes

Out[28]:

	id	name	minutes	contributor_id	submitted	tags	nutrition	n_steps
0	333281	1 brownies in the world best ever	40	985201	2008-10- 27	['60- minutes-or- less', 'time- to-make', 'cour	[138.4, 10.0, 50.0, 3.0, 3.0, 19.0, 6.0]	10
1	453467	1 in canada chocolate chip cookies	45	1848091	2011-04- 11	['60- minutes-or- less', 'time- to-make', 'cuis	[595.1, 46.0, 211.0, 22.0, 13.0, 51.0, 2	12
2	306168	412 broccoli casserole	40	50969	2008-05- 30	['60- minutes-or- less', 'time- to-make', 'cour	[194.8, 20.0, 6.0, 32.0, 22.0, 36.0, 3.0]	6
3	286009	millionaire pound cake	120	461724	2008-02- 12	['time-to- make', 'course', 'cuisine', 'prep	[878.3, 63.0, 326.0, 13.0, 20.0, 123.0,	7
4	475785	2000 meatloaf	90	2202916	2012-03- 06	['time-to- make', 'course', 'main- ingredient'	[267.0, 30.0, 12.0, 12.0, 29.0, 48.0, 2.0]	17
83777	486161	zydeco soup	60	227978	2012-08- 29	['ham', '60-minutes-or-less', 'time-to-make'	[415.2, 26.0, 34.0, 26.0, 44.0, 21.0, 15.0]	7
83778	493372	zydeco spice mix	5	1500678	2013-01- 09	['15- minutes-or- less', 'time- to-make', 'cour	[14.8, 0.0, 2.0, 58.0, 1.0, 0.0, 1.0]	1
83779	308080	zydeco ya ya deviled eggs	40	37779	2008-06- 07	['60-minutes-or-less', 'time-to-make', 'cour	[59.2, 6.0, 2.0, 3.0, 6.0, 5.0, 0.0]	7

	id	name	minutes	contributor_id	submitted	tags	nutrition	n_steps
83780	298512	cookies by design cookies on a stick	29	506822	2008-04- 15	['30- minutes-or- less', 'time- to-make', 'cour	[188.0, 11.0, 57.0, 11.0, 7.0, 21.0, 9.0]	9
83781	298509	cookies by design sugar shortbread cookies	20	506822	2008-04- 15	['30-minutes-or-less', 'time-to-make', 'cour	[174.9, 14.0, 33.0, 4.0, 4.0, 11.0, 6.0]	5

83782 rows × 20 columns

The question we are going to research on is that: are regular recipes and complex recipes are rated in the same scale?

In this part, we will define a complex recipes as recipes have greater than 10 steps. We will conduct a permutation test.

Null Hypothesis H0: People are rating all the recipes in the same scale.

Alternative Hypothesis H1: People are giving complex recipe lower rating

The reason for choosing one-sided test is that we might assume people could feel frustrated when cooking complex recipes, and also recipes with more steps are harder to cook

```
In [29]: # keep only useful column, including n_steps and average rating
    df_testing = recipes[['id', 'n_steps', 'ave_rating']]
    df_testing = df_testing.dropna()
    df_testing['complex'] = df_testing['n_steps'] > 10
    obs_df = df_testing.groupby('complex').mean()
    obs_df
```

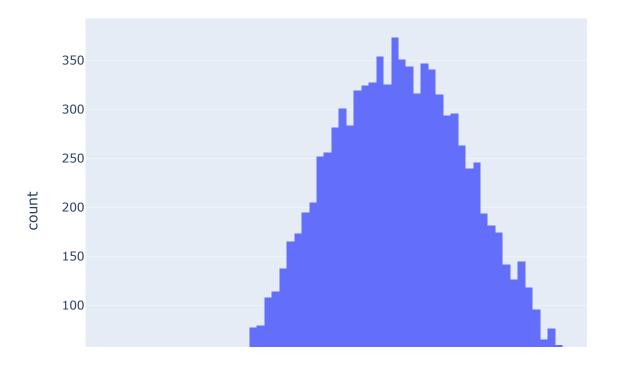
Out[29]:

	id	n_steps	ave_rating
complex			
False	378151.284947	6.357180	4.501838
True	385033.935788	16.141415	4.484409

Since ave\_rating is numerical data, so it is proper to use the difference in mean,

```
In [30]: obs = obs_df['ave_rating'].iloc[0] - obs_df['ave_rating'].iloc[1]
    obs
Out[30]: 0.017428379224658563
```

```
In [31]: lst = []
    for i in range(10000):
        df_testing = df_testing.assign(permuted = np.random.permutation(df_testing['compl
        temp = df_testing.groupby('permuted').mean()
        diff = temp['ave_rating'].iloc[0] - temp['ave_rating'].iloc[1]
        lst.append(diff)
        arr = np.array(lst)
```



```
In [33]: p_value = (arr > obs).mean()
p_value

Out[33]: 0.0009
```

Since the p-value is larger than the significant level, which is 0.05, we fail to reject the null hypothesis. This result could be reasonable since first, the complexity of a recipes does not decide whether the food is delicious or not. The taste of the food, which is one important part of the rating, is not likely to be determined by the complexity of recipe. On the other hand, another

possible explanation could be different people might have various opinions towards the complexity of the recipe. Some might prefer simple recipes since they are convenient and time-saving. Others could love the process of cooking and enjoy working a complex recipes.

In	[	]:	