**1 DATASETS**

We have access to order fleet, which is from ele.me company. Our datasets contain order detail amongest holiday, not holiday, weekday and weekend. The details about the data are given in Table. 1.

Table. 1. Life Flow of An Order

|  |  |
| --- | --- |
|  | **Order** |
| Data Size | 3 thousand |
| # of Daily Records | 3 hundred |
| Format | Rider ID& Order ID& Shop ID  User& Shop GPS  Timesteps: Shop Accept Order & Rider Accept Order, Arrive Shop , Pick Up, Arrival User  Sku ID |

**• Order:** The data we get was collected from the company’s database, collecting method and datasets’ format are similar with datasets in dataAnalysis1.0. The only difference that need to be notice is that skuID is the identification of one dishe in one order.

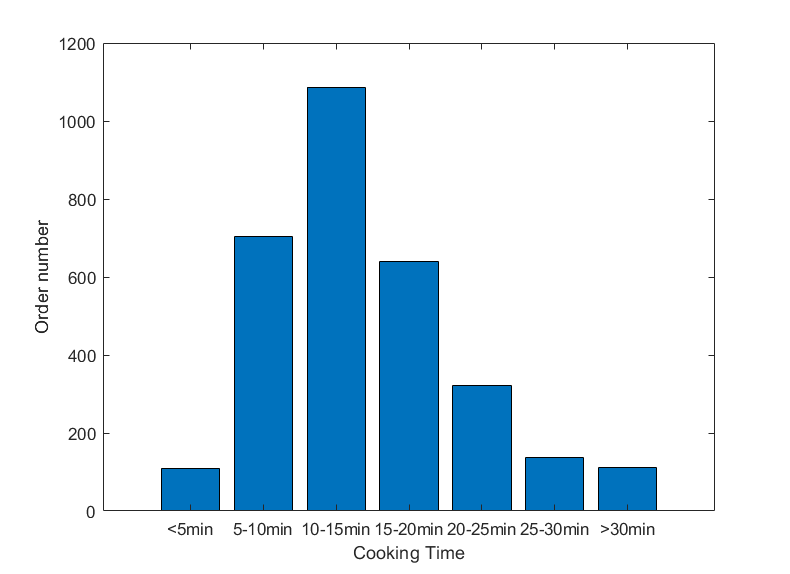
**2 METHODOLOGY**

**Same method with dataAnalysis2.0(Addition: SkuID are matched with order)**

**3 MEASUREMENT RESULTS AND ANALYSIS**

In this section, we generally divide the Cooking Time into five levels <5min, 5min, 10min, 20min, 20-25min, 25-30min, >30min. The order number in different levels are shown in Fig.1.

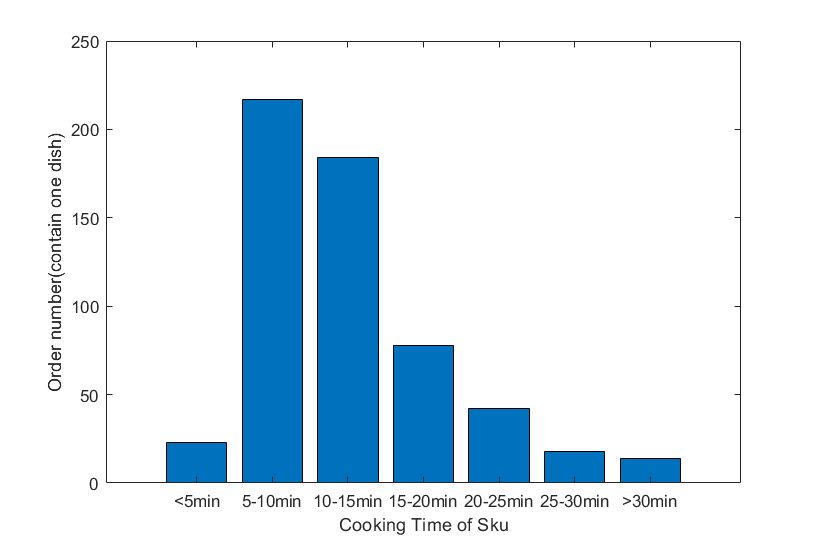
Fig. 1. Cooking Time



The proportion of cooking time less than 5’ or more than 30’ orders are less than 10%.

After that we also select all orders which only contain one dish, we assume that order making time are the cooking time of dish. The order number (contain one dish) in different levels are shown in Fig.2.

Fig. 2. Cooking Time of Sku



**However, we find there are some issues in raw data which cause the minimum cooking time in our datasets is 44’’ and there are 2 order use less than 1 minute cooking time.**

**6.1 Anomalies**

We list the investigated anomalies in two categories, i.e., expected and unexpected anomalies, in Table. 2.

Table 2. Anomaly Examples

|  |  |
| --- | --- |
| **Anomaly Category** | **Anomaly Exmples** |
| Expected | festival, special order dishes |
| Unexpected | Order time less than one minute |

6.1.1 Less than one minute. Company ele.me tell us they do not record any canceled order, so orders in our datasets are all effective. Therefore, we get corresponding rider gps trace for each anomaly orders. The format is same with rider date in dataAnalysis1.0.

(i) *Calculation*. We firstly calculate cooking time for all orders use method in dataAnalysis2.0. Then we sort the data we get by time. We collect data items which contains less than one minutes cooking time and add them into cooking time table. Cooking time table is shown in Table. 3.

Table 3. Cooking Table

|  |  |
| --- | --- |
|  | **Order detail** |
| Format | Order ID& **Rider ID** &  Timesteps: Shop Accept Order & Rider Pick Up  Cooking Time |

(ii) *Structuralizing*. We cast the raw data into a table that contain 5 key attributes,ie.,[OrderID, RiderID, Shop Accept Order(timestamp), Pick Up(timestamp), Cooking time(calculated)]. By this approach, we focus on the cooking time and use the Rider ID to match GPS trace data. We show the samples of the table of cooking time anomaly in Table. 4.

Table 4. Anomaly Examples

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Order ID** | **Rider ID** | **Shop Accept Order** | **Rider Pick Up** | **Cooking Time(s)** |
| 68fd222e | f883fdd33 | 2018-9-28 14:17 | 2018-9-28 14:18 | 44 |
| 2139fd429 | 00be12ee | 2018-10-3 20:17 | 2018-10-3 20:18 | 59 |
| 3e0d4a64 | 00be12ee | 2018-9-27 13:06 | 2018-9-27 13:07 | 79 |

(iii) *Matching*. Using Rider ID and corresponding timestamps, we get rider GPS trace from our datasets. Finally, we draw rider GPS track map at the delivering time. The track maps of three riders in sample are shown in Fig.3.

Fig. 3. Rider GPS track maps

|  |  |  |
| --- | --- | --- |
| |  |  | | --- | --- | | Rider: 00be12ee Time: 20180927 | Rider: 00be12ee Time: 201801003  Rider: f883fdd33 Time: 20180928 | |

Distance from shop to costume location are less than 200 meters, travel time less than one minute is acceptable for these situation.