Practical Approach to Evacuation Planning Via Network Flow and Deep Learning

Akira Tanaka※ Nozomi Hata※

Nariaki Tateiwa※ Katsuki Fujisawa †

※ Graduate School of Mathematics, Kyushu University

† Institute of Mathematics for industry, Kyushu University

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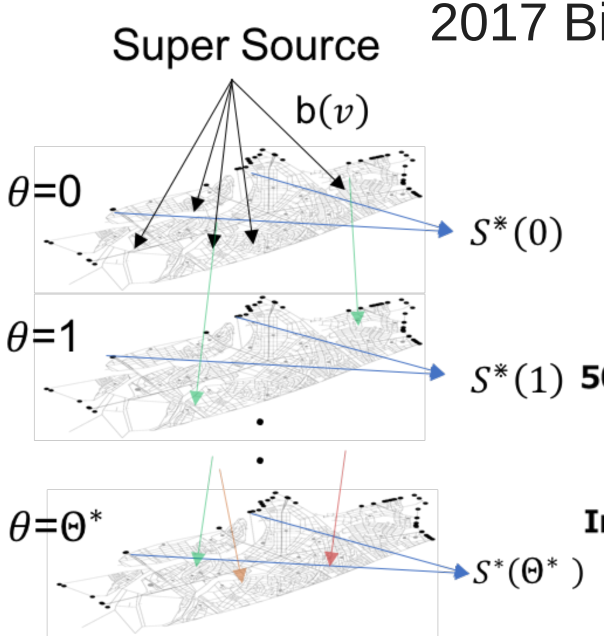
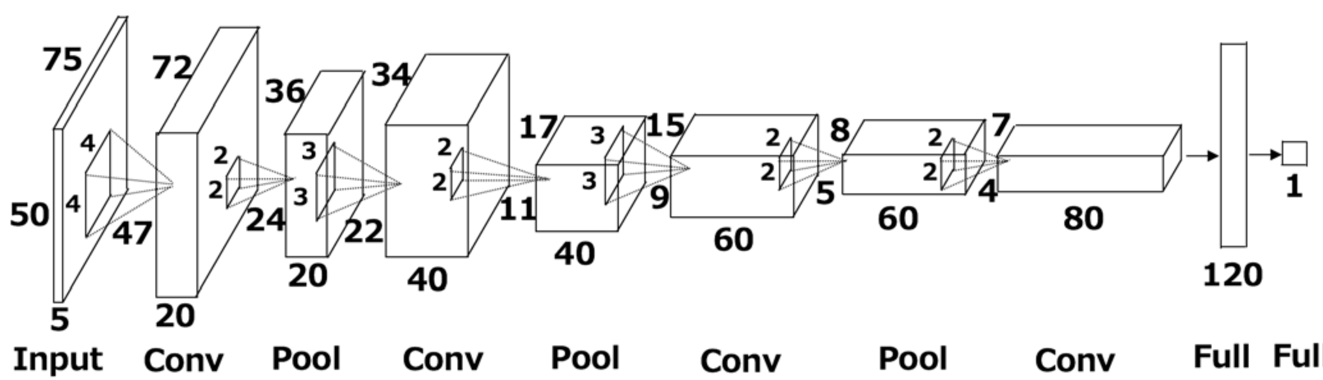




Evacuation Map

Yodogawa Area in Osaka City

#nodes : 2,933

#edges : 8,924

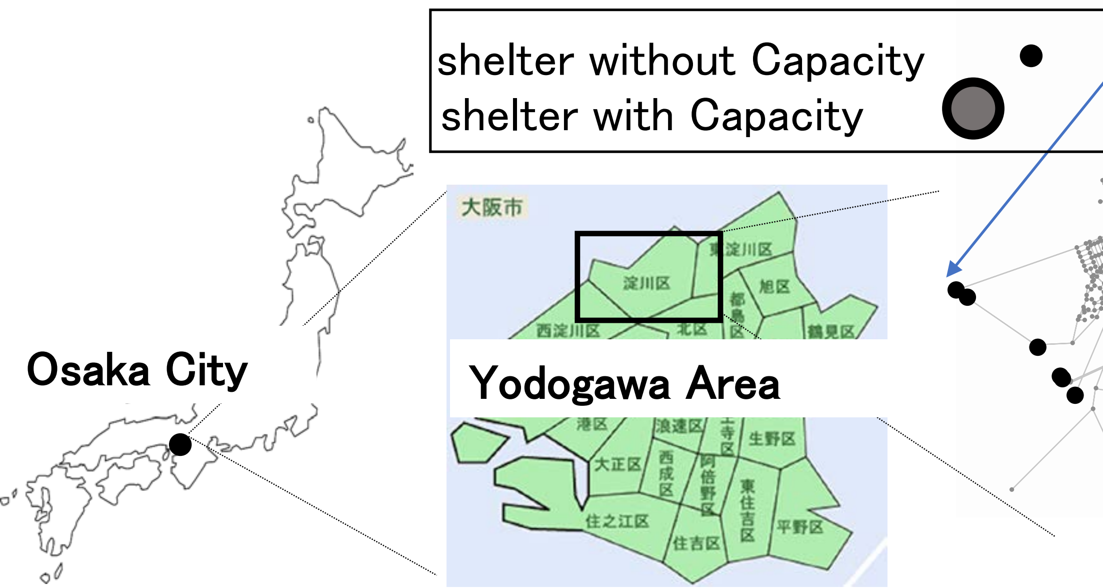
#evacuees : 50,000 ~ 80,000 ← Based on midnight population

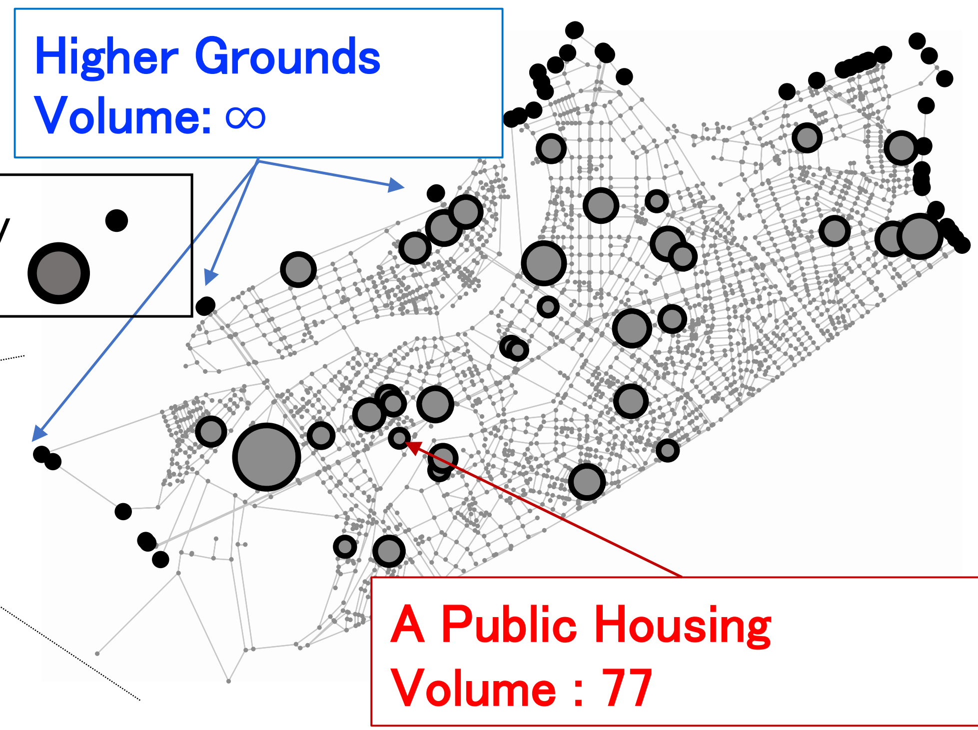
#shelters

- with finite capacity : 36 (total volume:35,549)
- with infinite capacity : 50 (each volume:∞)

Higher Grounds

Tall and Strong Buildings

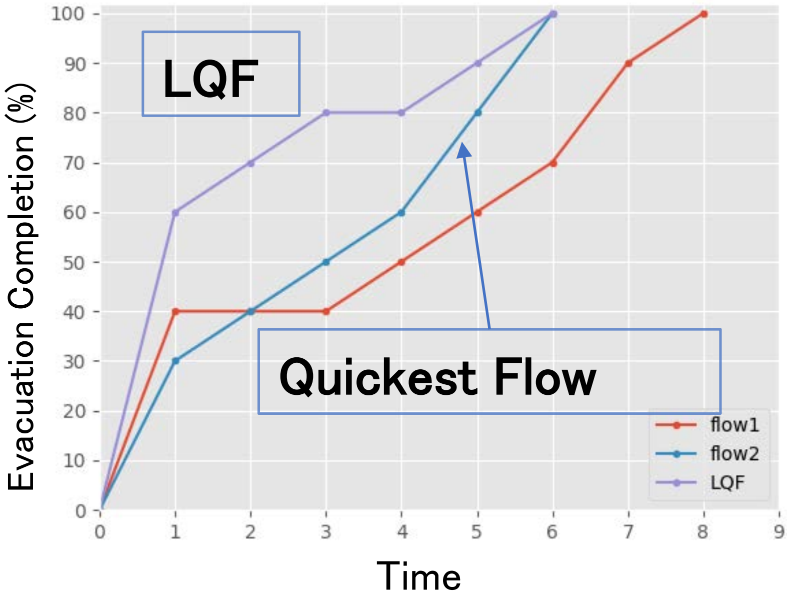




Lexicographically Quickest Flow(LQF)

Definition

- Minimizes the evacuation time Θ^*
- Greedily maximize the cumulative number of evacuees who have already completed evacuation at every time θ in the order of $\theta = 1,2,..,\Theta^*$



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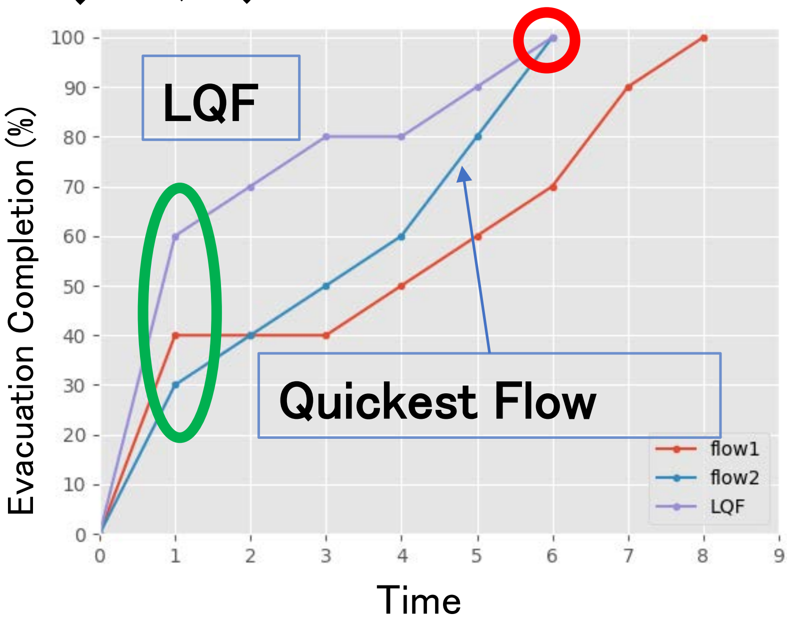

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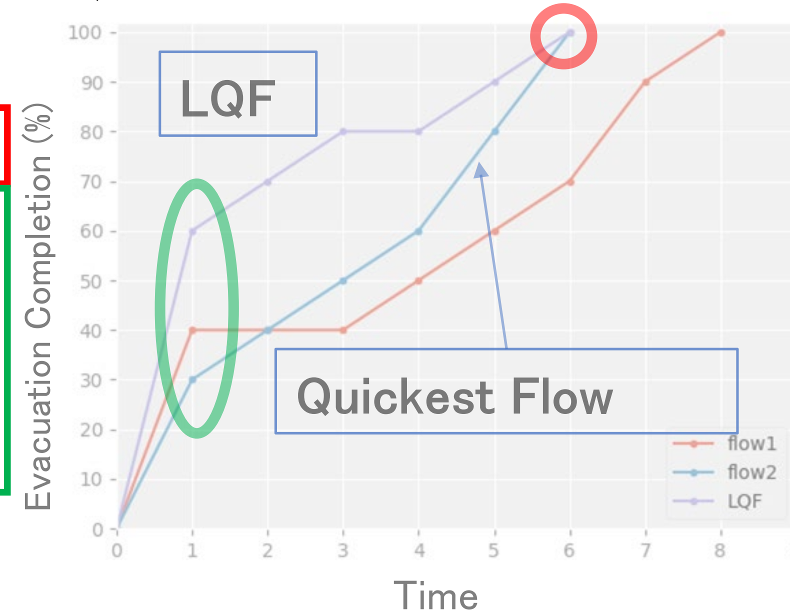


Practical Property

- The LQF also has a high efficiency with respect to total pedestrian flow of all evacuees to the refuges
- To check this property, we decomposed the LQF into cyclic flow and cycle-free flow by solving the QP below:

Flow f

Cyclic Flow f_c
(only 2 cycles remained)

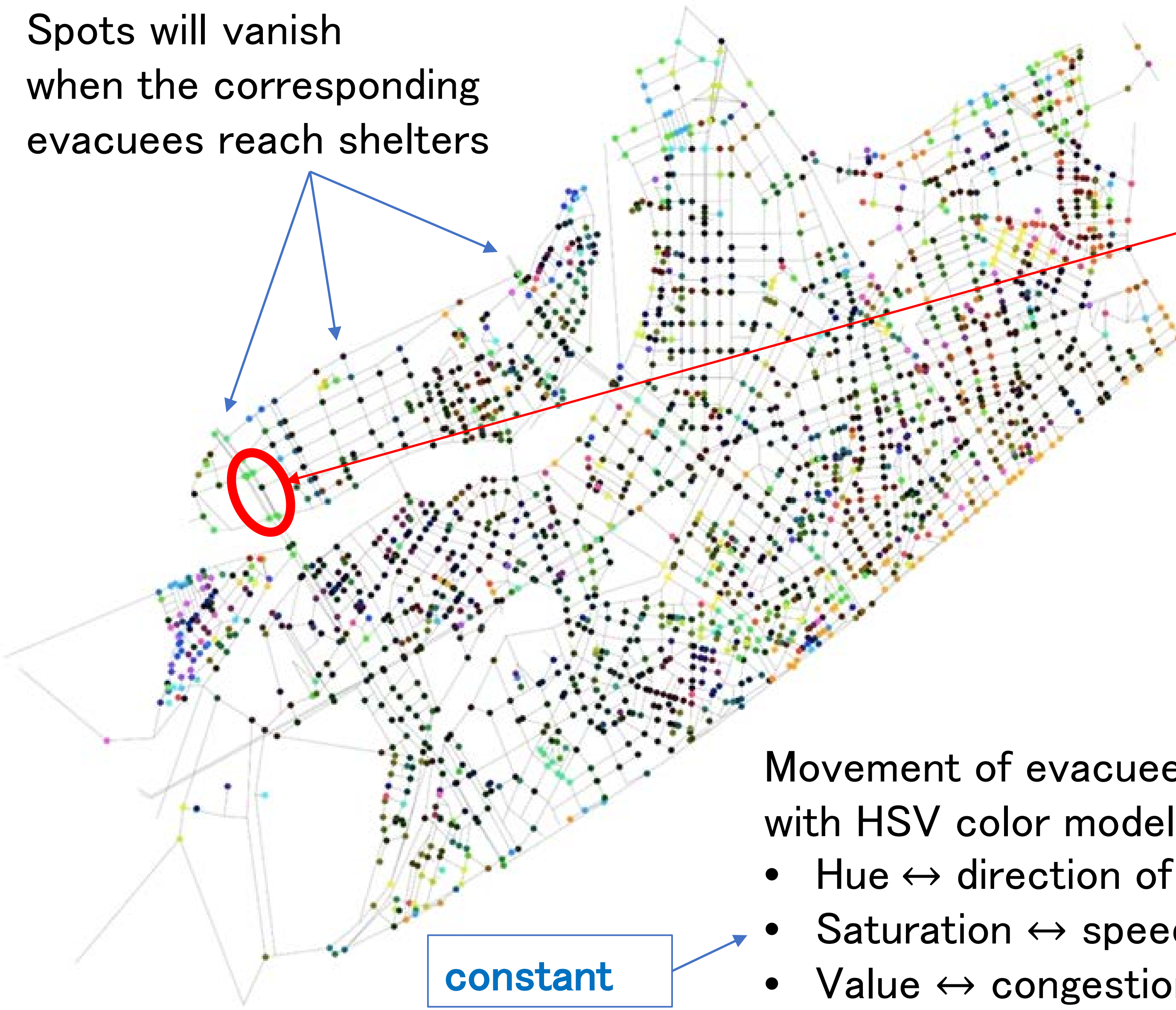
$$
\begin{aligned}
\text{minimize} \quad & \sum_{e\in A}(f(e)-f_c(e))^2 \\
\text{subject to} \quad & f_c \in \mathcal{F}_c \\
& 0 \le f_c(e) \le f(e) \qquad (\forall e \in A \text{ s.t. } f(e) \ge 0) \\
& f(e) \le f_c(e) \le 0 \qquad (\forall e \in A \text{ s.t. } f(e) \le 0)
\end{aligned}
$$

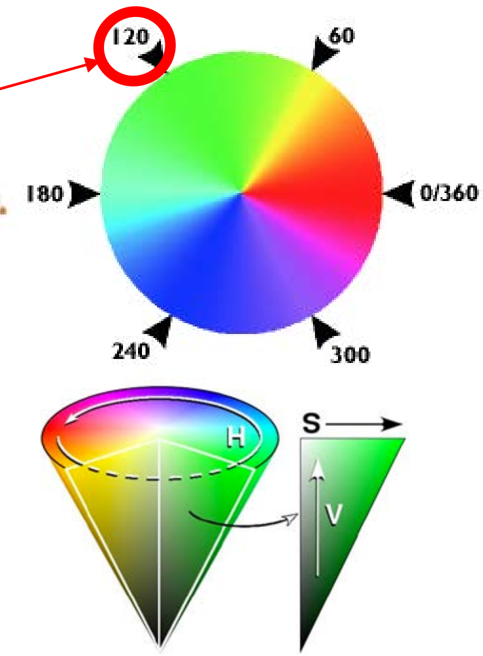
where

- $f(e)$ is the total refuges that passed the arc e
- $A:$ the set of arcs
- $\mathcal{F}_c := \{f : A \to \mathbb{R} \mid f \text{ is a cyclic flow}\}$

Visualization of LQF

Spots will vanish
when the corresponding
evacuees reach shelters





Movement of evacuees are expressed with HSV color model

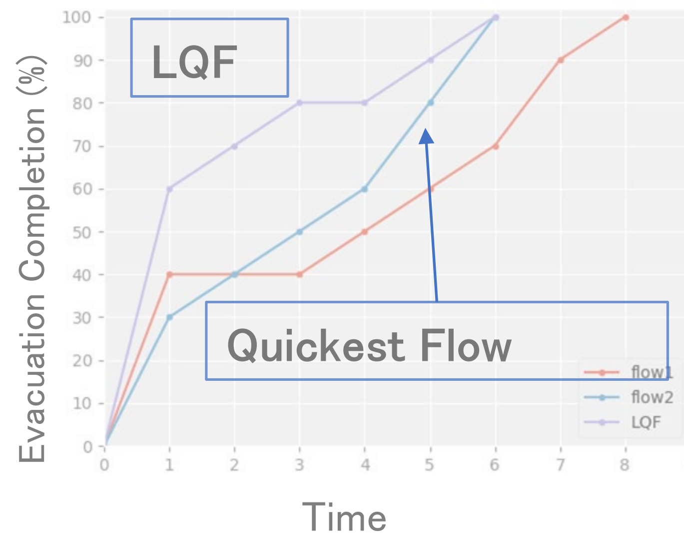
- Hue ↔ direction of movement
- Saturation ↔ speed of movement
- Value ↔ congestion of arc

constant

Lexicographically Quickest Flow (LQF)

Pros(practical property)

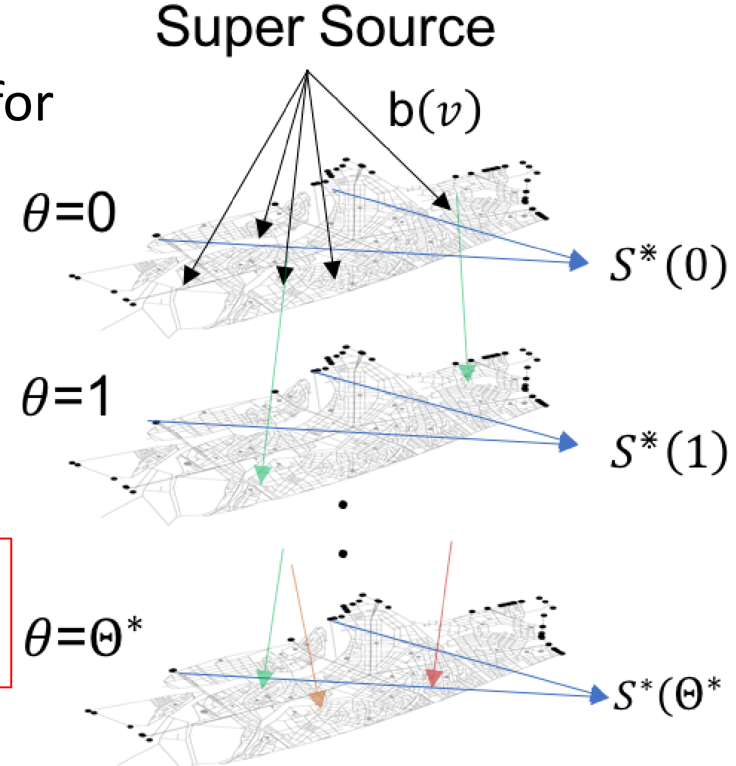
- Minimizes the evacuation time Θ^*
- Greedily maximize the cumulative number of evacuees
  →More people reach shelters in the early stage
- There are few unnecessary movements



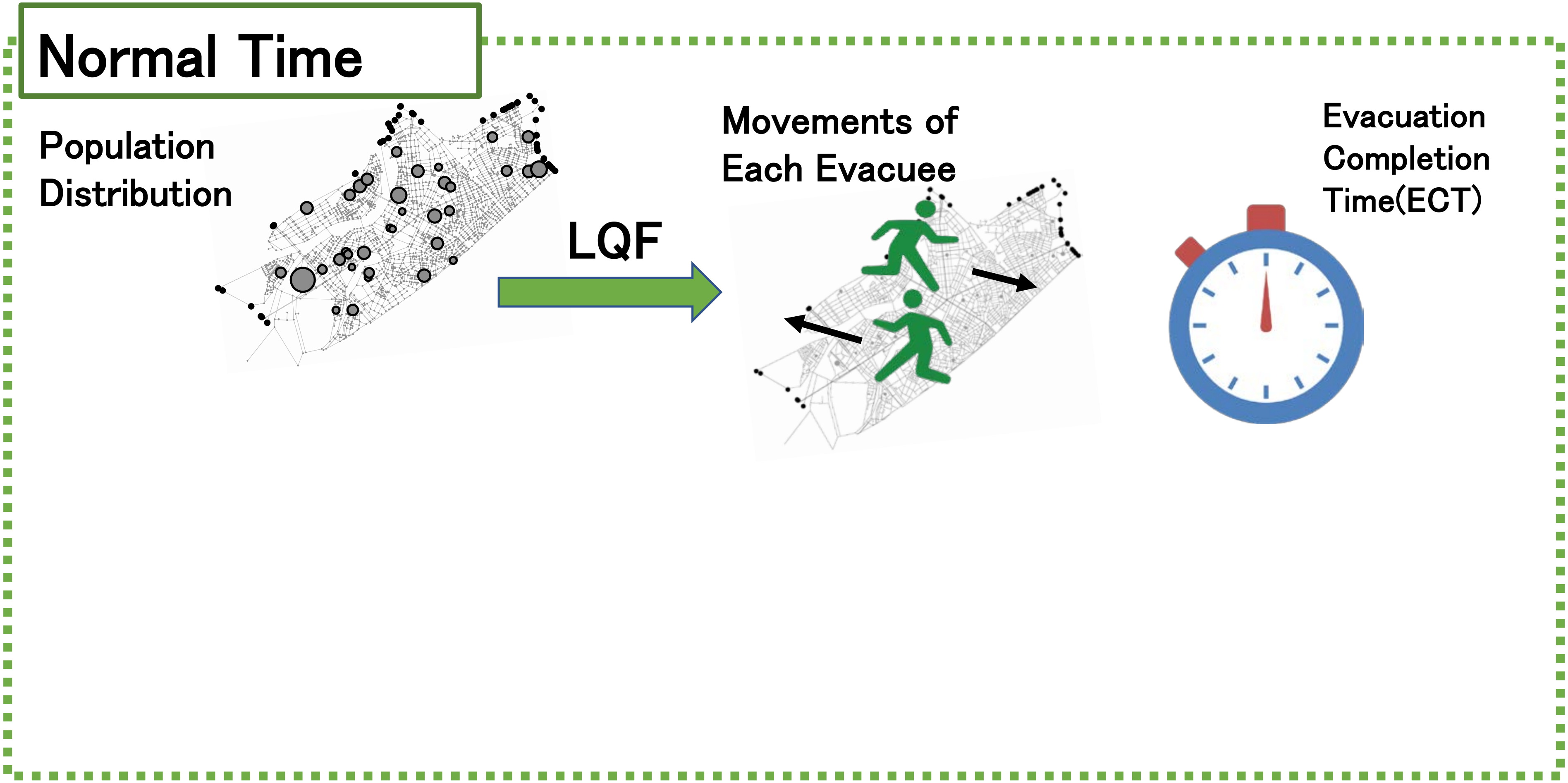
Cons

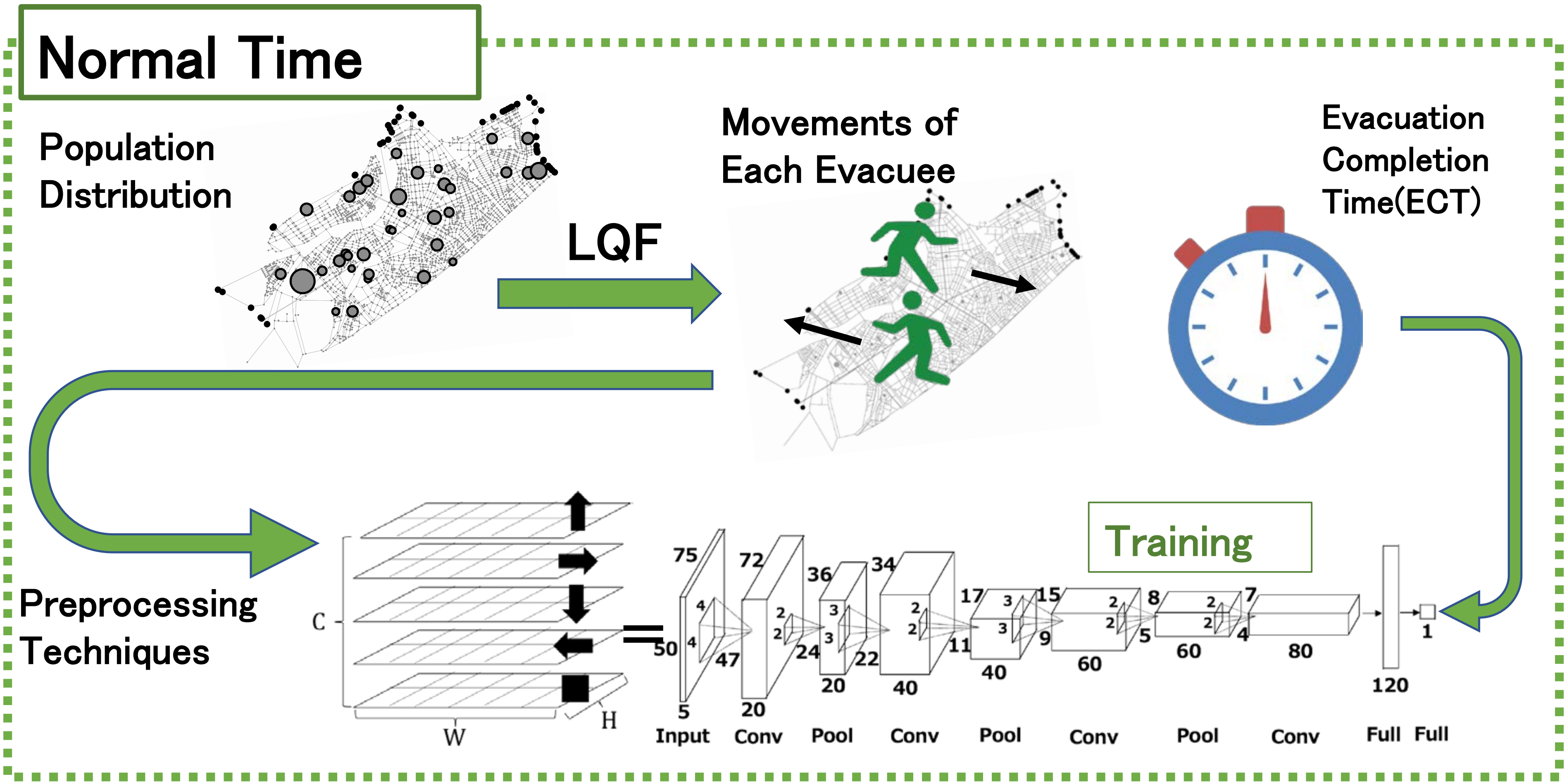
- Not practical(7h for the target area)
  - Compute the maximum flow repeatedly for the time-expanted graph.
  - Size of time-expanded graph is huge

	Original	Time-Expanded($\theta = 2,824$)
#nodes	2,933	8,300,000
#edges	8,924	32,800,000



To utilize practical property of LQF, we combine it with Deep Learning


Normal Time
Population Distribution
LQF
Movements of Each Evacuee
Evacuation Completion Time(ECT)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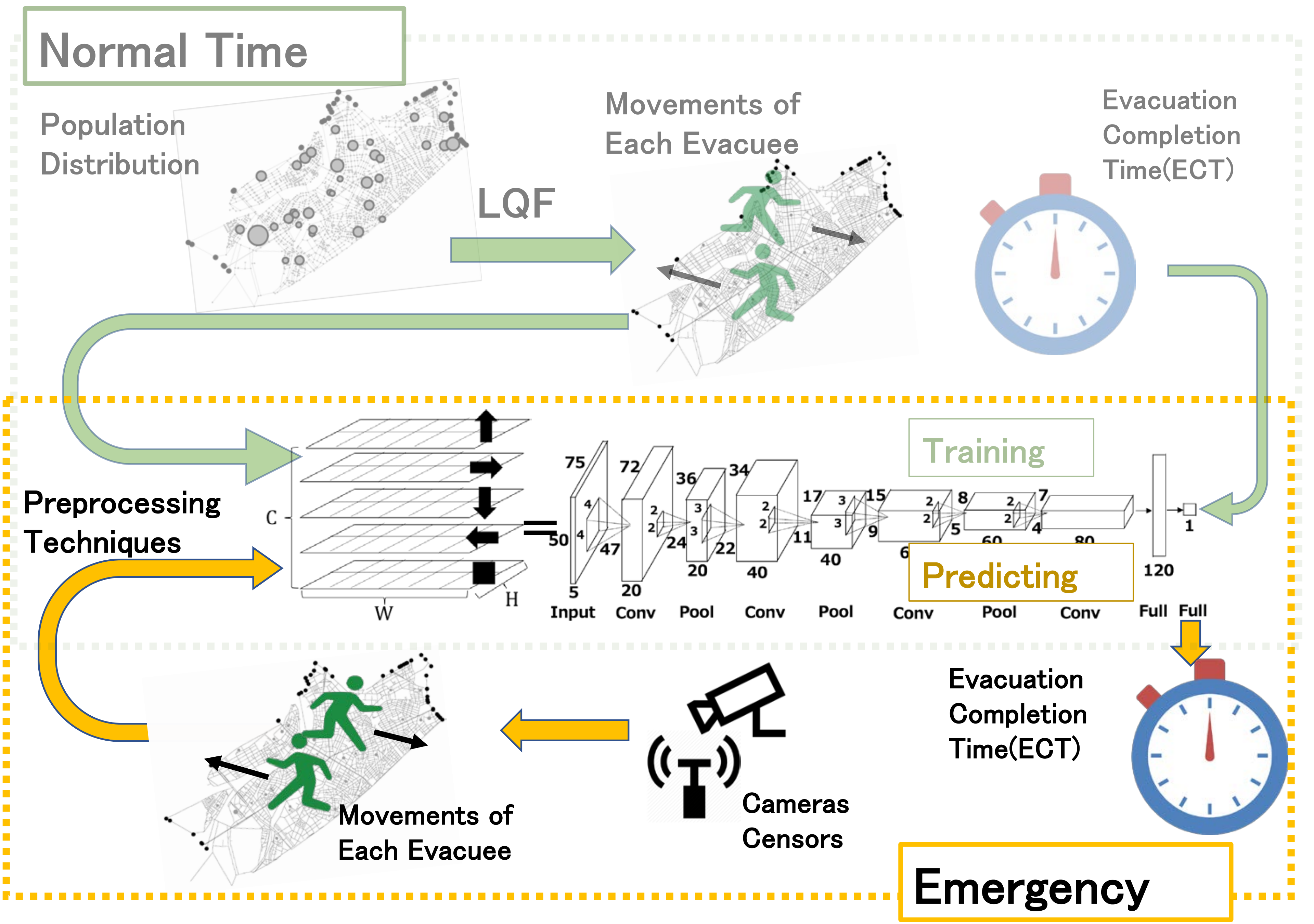
Preprocessing Techniques
Training
C
W
H
Input
Conv
Pool
Conv
Pool
Conv
Pool
Conv
Full
Full



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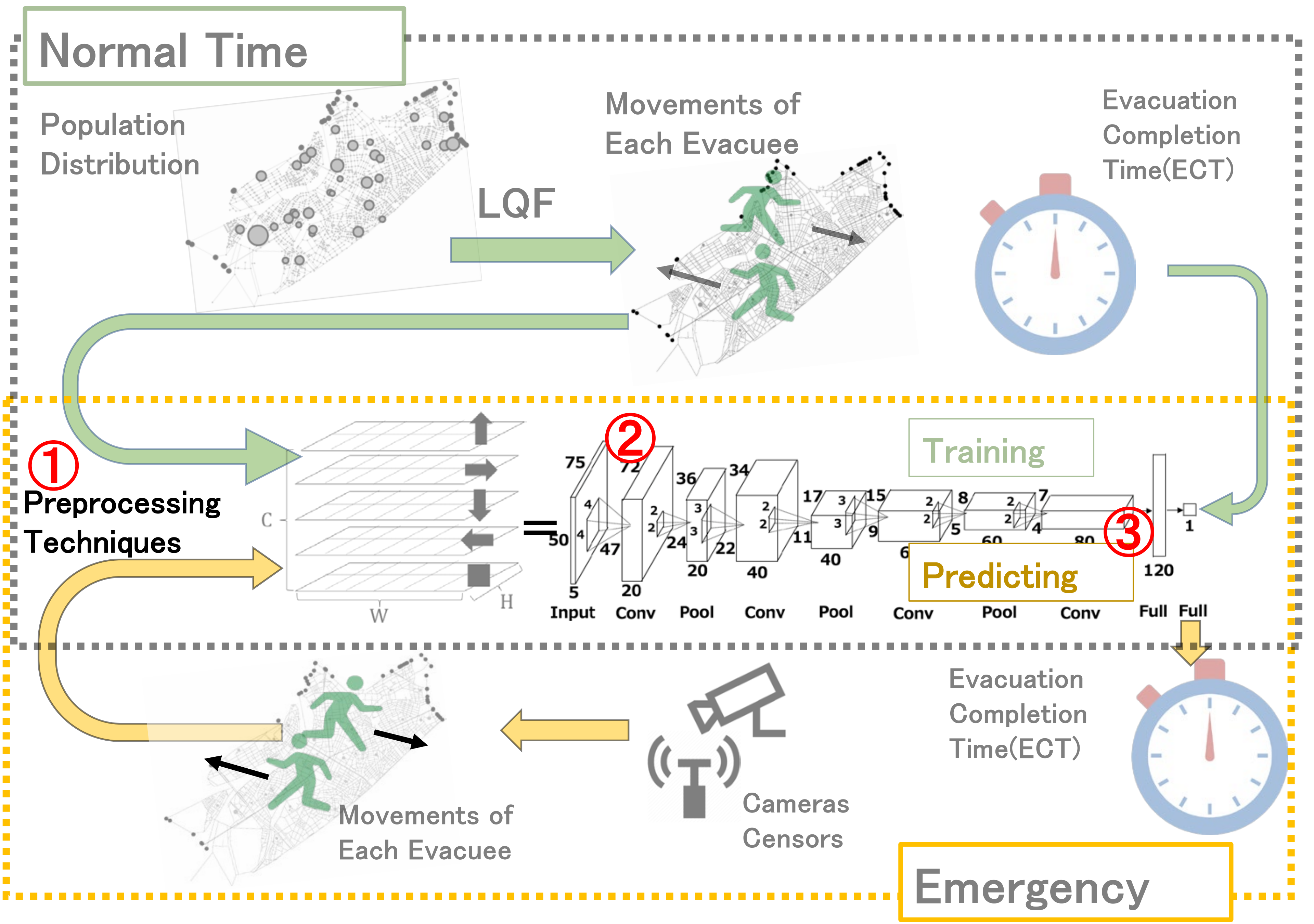
Evacuation Completion Time(ECT)
Cameras Censors
Movements of Each Evacuee
Emergency



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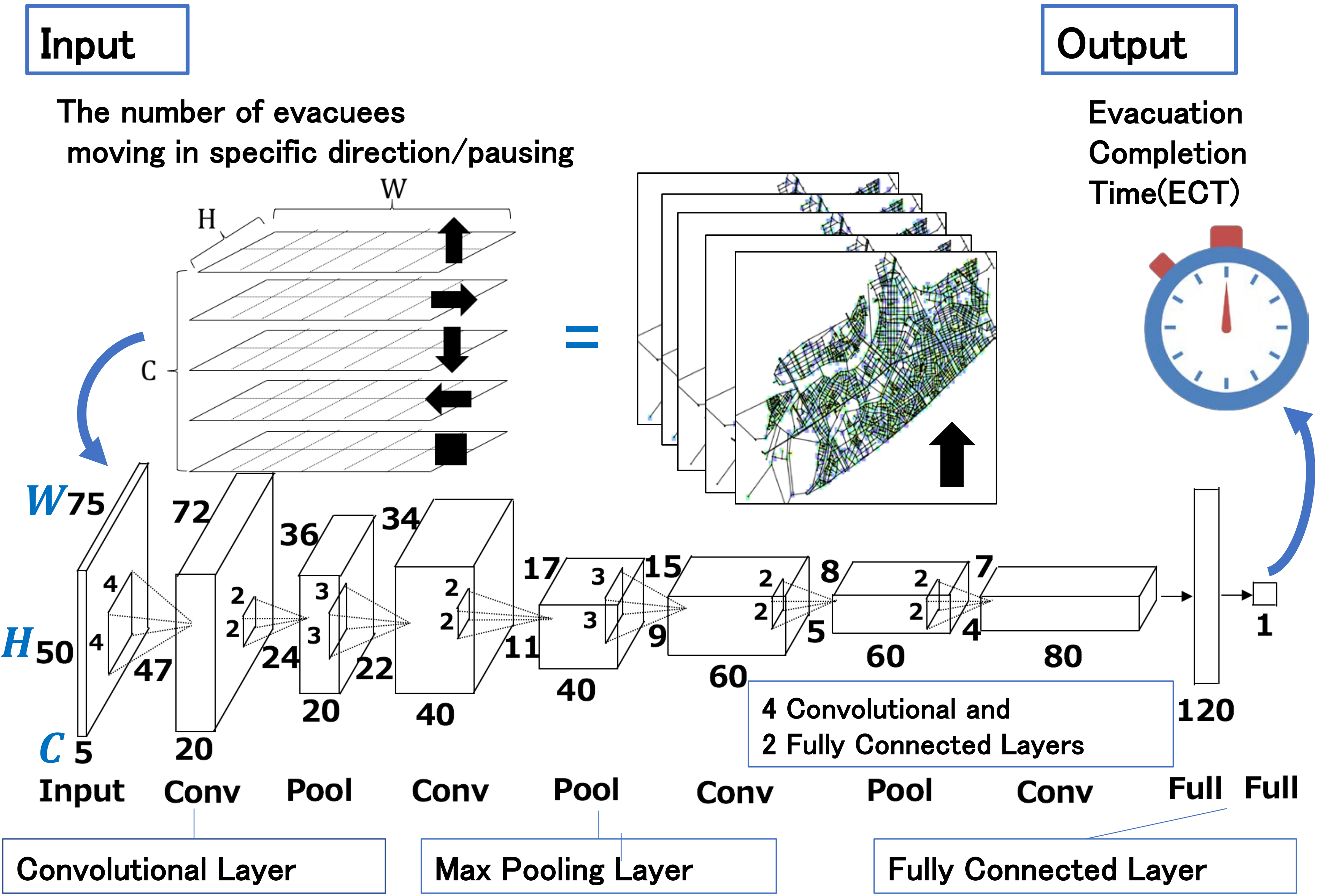
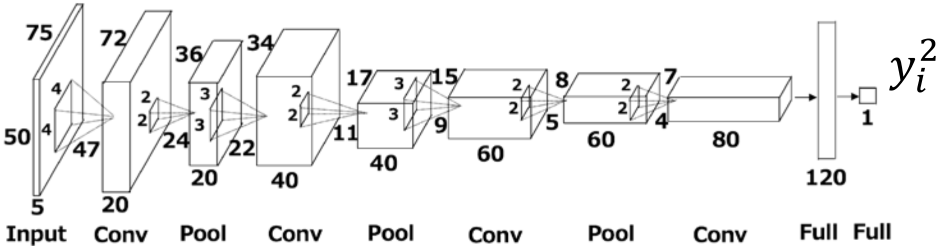
Convolutional Neural Network(CNN)



Optimizer and Output of CNN



Euclidean Loss (cost function)

$$\frac{1}{2N}\sum_{i=1}^{N}\left\|y_i^1 - y_i^2\right\|^2$$

y_i^1:Accuare output(LQF_T)
y_i^2:Predicting output
N:data size

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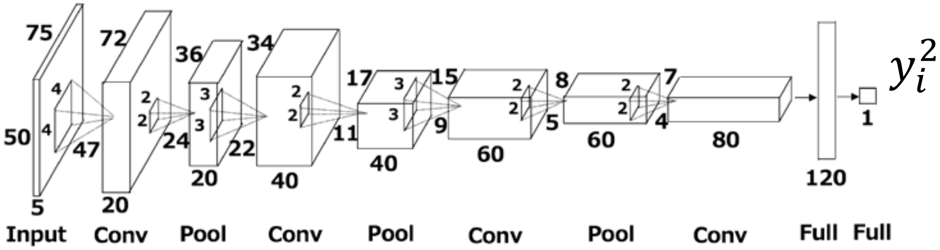

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Adam(optimizer)

- First-order gradient-based optimization

→ feasible to compute in practice for high-dimensional data

- Storing exponentially decaying average of past gradient and squared gradient

→Large updates for infrequent and smaller updates for frequent
→accelerate learning

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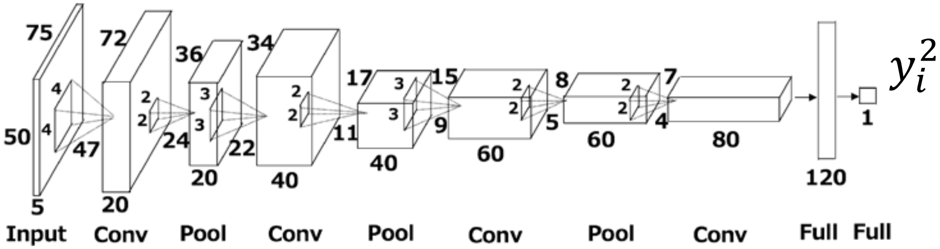

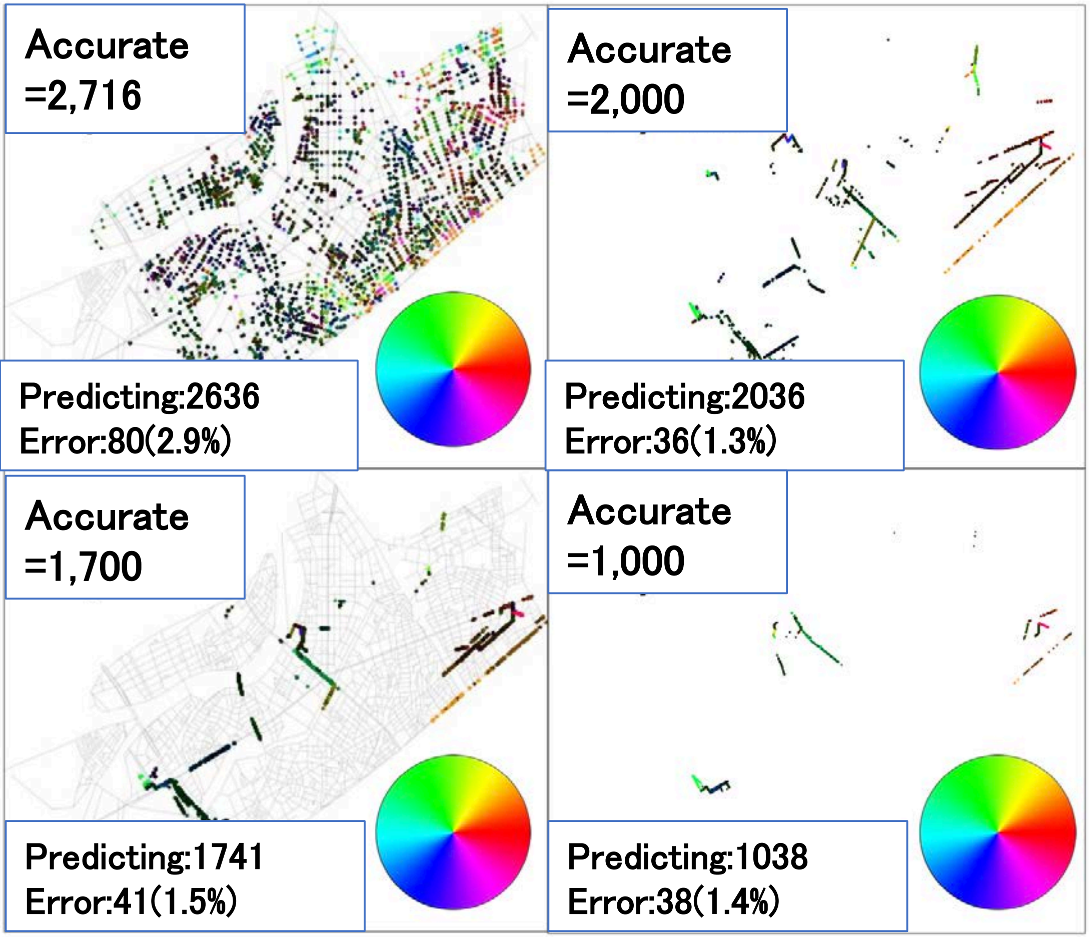

Error := |Accurate − Predicting| (Error / 2,751)
Note: 2,751 is the average evacuation time

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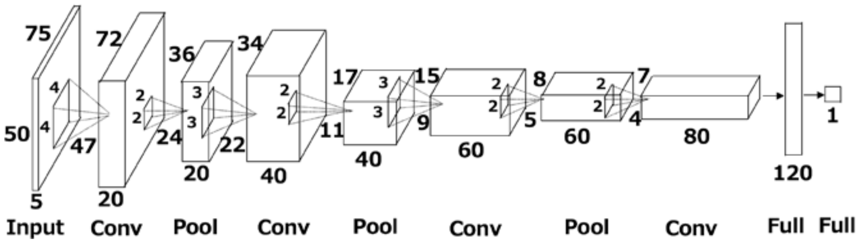
Results of Our Model

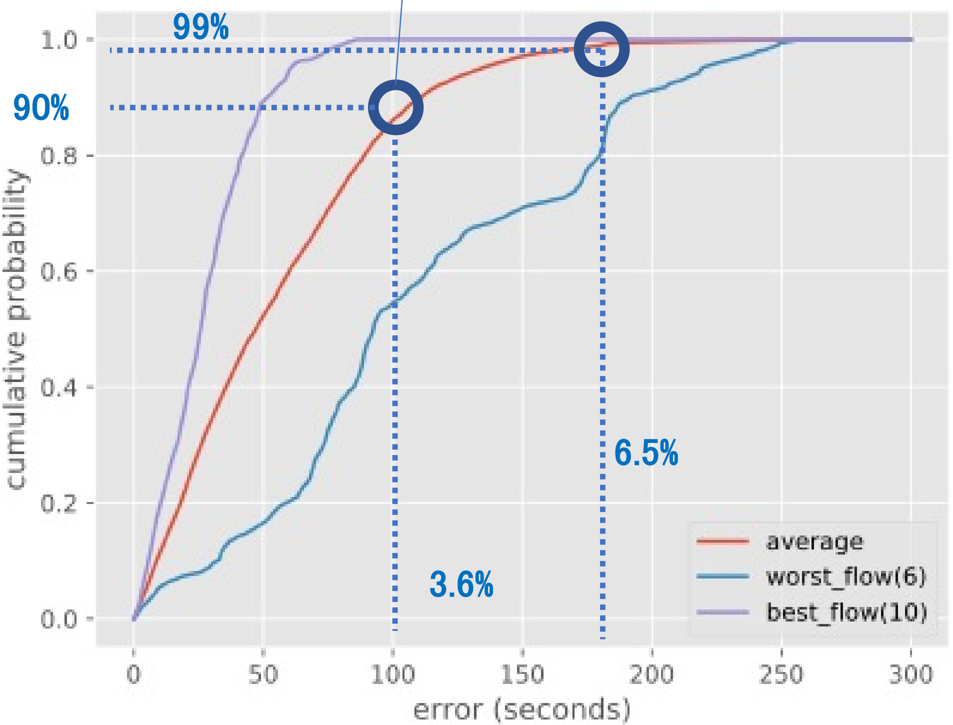
Data

#Training Data: 43,200

#Test Data: 5,400



90% probability that we make prediction within 3.6% error



Cumulative Probabilities

Results of Our Model

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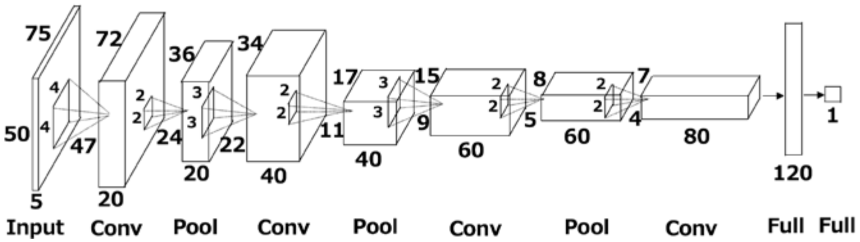
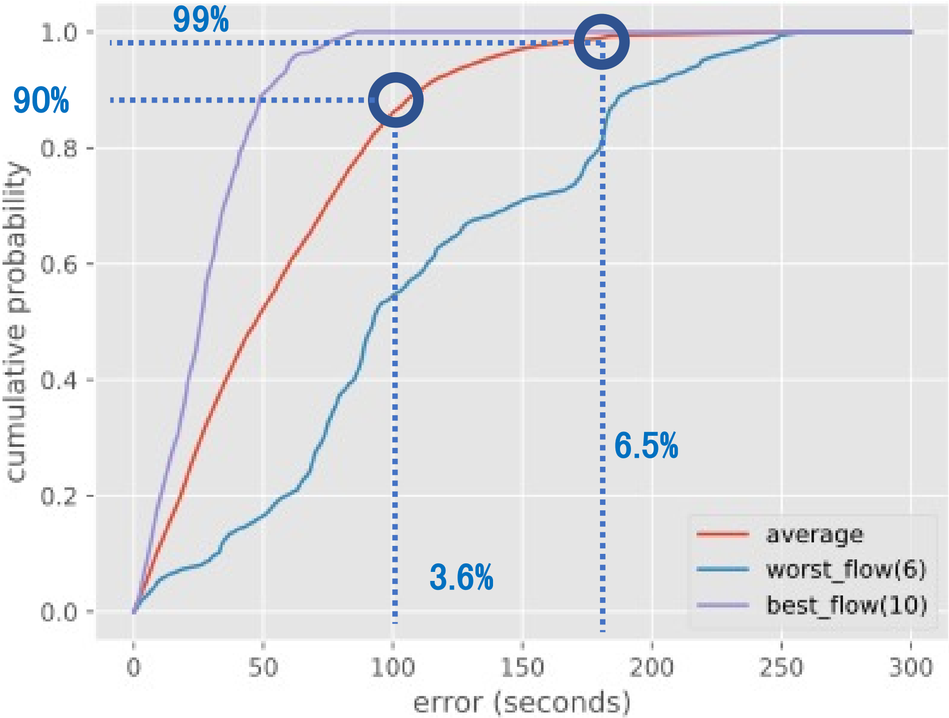


90% probability that we make prediction within 3.6% error

Average error(55s 2%) is quite a small

Prediction for the early stage is better than that for the final stage



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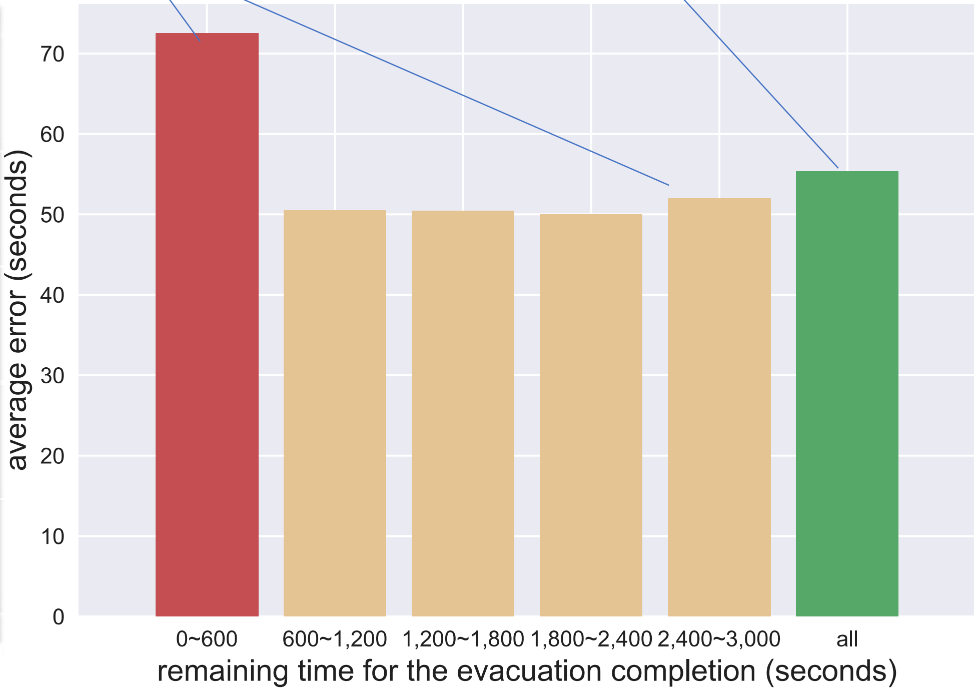

Average Error in Several Stages of Evacuation

Summary

Previous Model(LQF)

Not practical(7h)

- Compute max-flow repeatedly for time-expanded graph
- Time-expanded graph is huge

Proposed Model

Practical (less than 1s)

- Combing LQF and CNN
- Predict evacuation completion time immediately(less than 1s) and almost accurately(2%)