# Understanding the Uncertainty in 1D Unidirectional Moving Target Selection

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INTRODUCTION

# MOVING TARGETS EVERYWHERE


Screenshot of StarCraft II

Computer game


www.foxsports.com

Future sports video sys

www.napolilaw.com

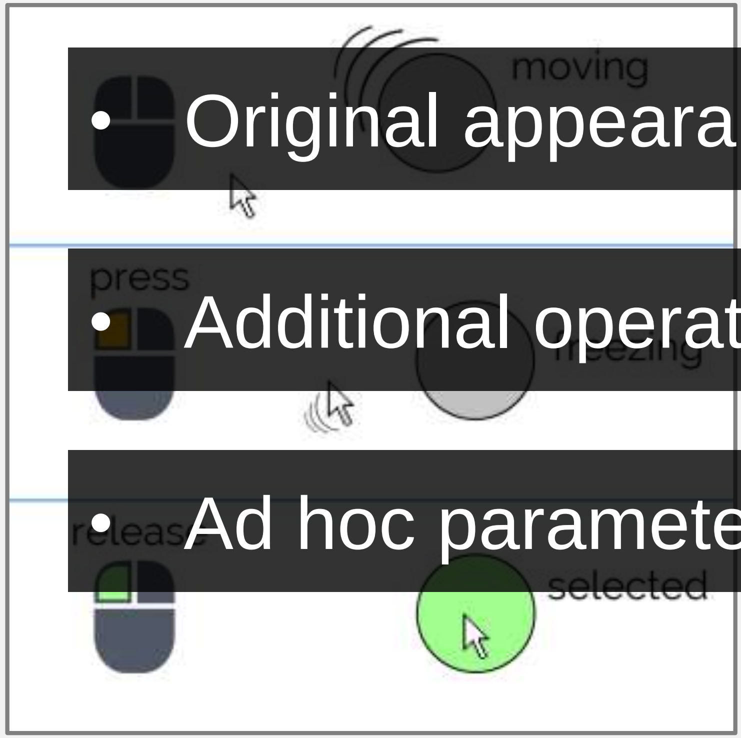
Air traffic control sys

# SELECTING MOVING TARGETS: A CHALLENGING TASK

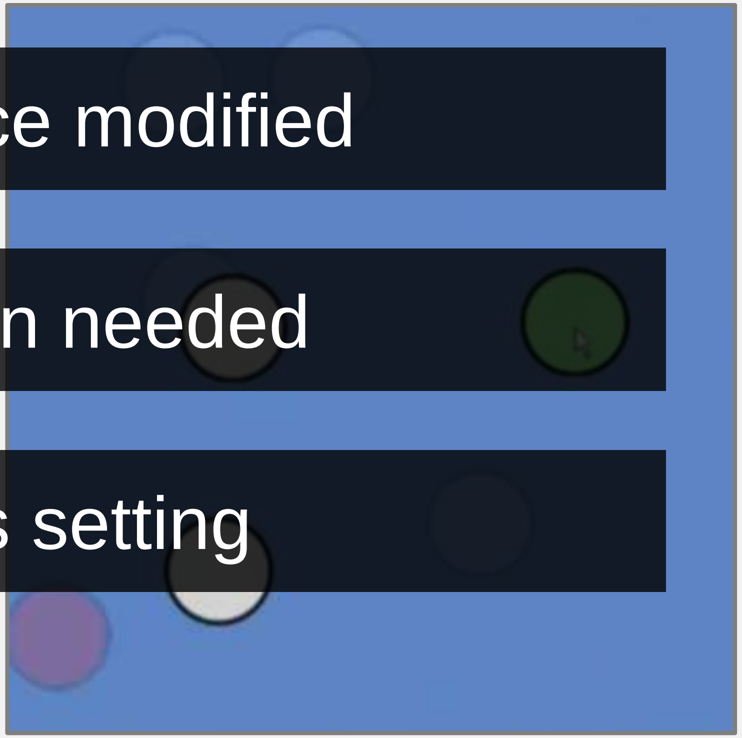
- A two-phase job: track and click
- Higher demand on sensory-motor system
- Worse user performances

# TECHNIQUES AND MODELS IN MOVING TARGET SELECTION

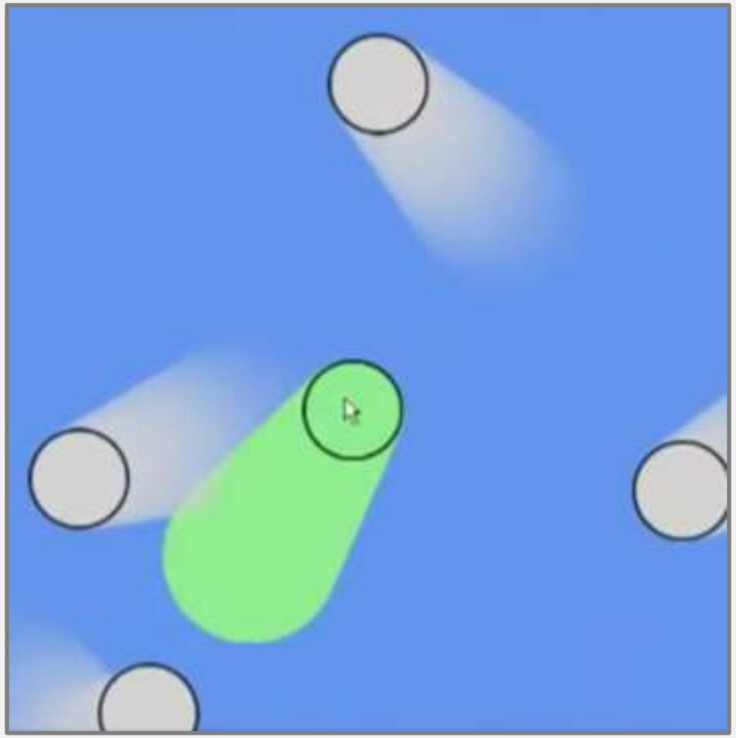
- Original appearance modified
- Additional operation needed
- Ad hoc parameters setting




**Hold** [Hajri 2011]



**Target Ghost** [Hasan 2011]



**Comet** [Hasan 2011]

# TECHNIQUES AND MODELS IN MOVING TARGET SELECTION

| | Static Targets | | Moving Targets |
|---|---|---|---|
| Movement Time | $$MT = a + b\log_2(\frac{A}{W}+1)$$ Fitts' Law [Fitts 1954] | | $$MT = a + bA + c(V+1)(\frac{1}{W}-1)$$ Jagacinski's model [Jagacinski 1980] |
| Endpoint Distribution | $$X \sim N(\mu,\sigma)$$ $$\mu = 0$$ $$\sigma = W/\sqrt{2\pi e}$$ Effective Width [A. T. Welford 1968] | $$X \sim N(\mu,\sigma)$$ $$\mu = c$$ $$\sigma = \sqrt{a+bW^2}$$ Dual-Gaussian Model [Bi 2013] | ? |

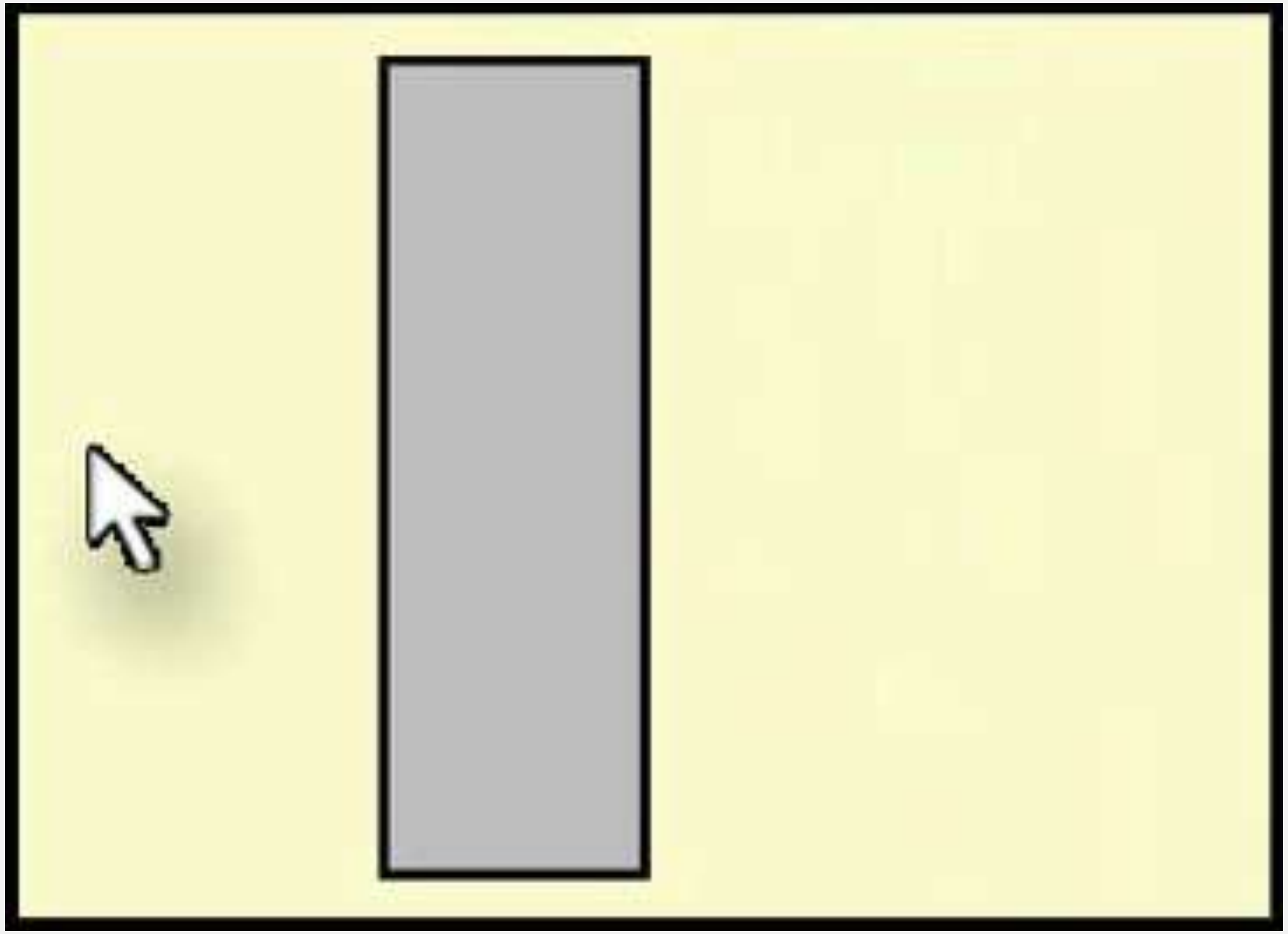
# TECHNIQUES AND MODELS IN MOVING TARGET SELECTION

| | Static Targets | Moving Targets |
| --- | --- | --- |
| Movement Time | $MT = a + b\log_2(\frac{A}{W} + 1)$ <br> Fitts' Law <br> [Fitts 1954] | $MT = a + bA + c(V + 1)(\frac{1}{W} - 1)$ <br> Jagacinski's model <br> [Jagacinski 1980] |
| Endpoint Distribution | $X \sim N(\mu, \sigma)$, $\mu = 0$, $\sigma = W / \sqrt{2\pi e}$ <br> Effective Width <br> [A. T. Welford 1968] <br><br> $X \sim N(\mu, \sigma)$, $\mu = c$, $\sigma = \sqrt{a + bW^2}$ <br> Dual-Gaussian Model <br> [Bi 2013] | $X \sim N(\mu, \sigma)$, $\mu = a + bV + cW$, $\sigma = \sqrt{d + eV^2 + fW^2 + g\frac{V}{W}}$ <br> This paper |

INTRODUCTION

# OVERVIEW OF OUR WORK

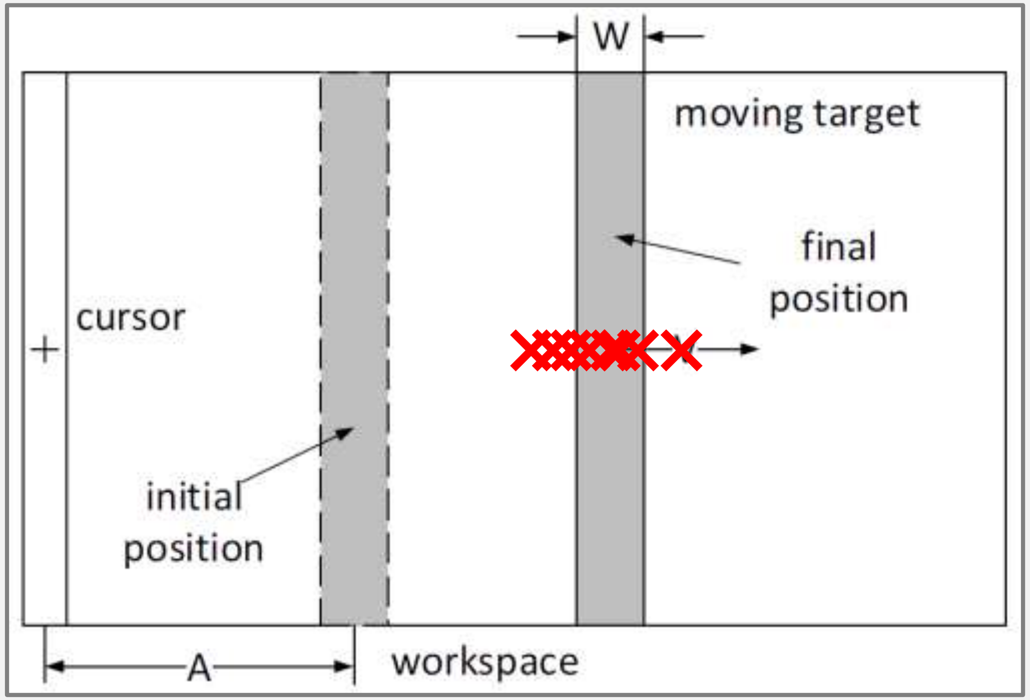
- The problem of modeling the endpoint distribution in 1D moving target selection
- A Ternary-Gaussian model to interpret the endpoint distribution
- Two model extensions:
    - 1) Error-Model
    - 2) BayesPointer



MODELING ENDPOINT DISTRIBUTION

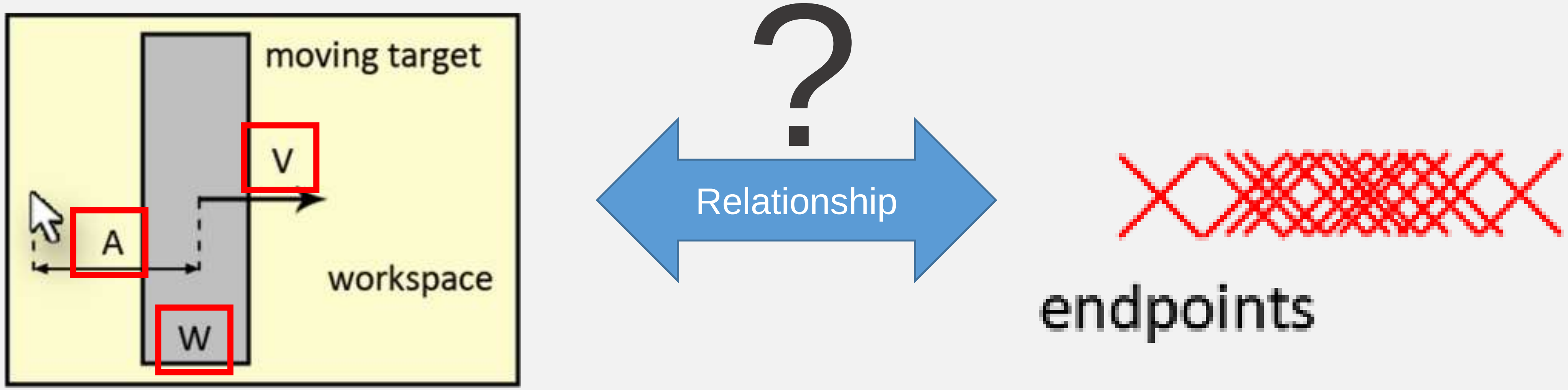
# PROBLEM DEFINITION

The task of 1D moving target selection




Experiment program

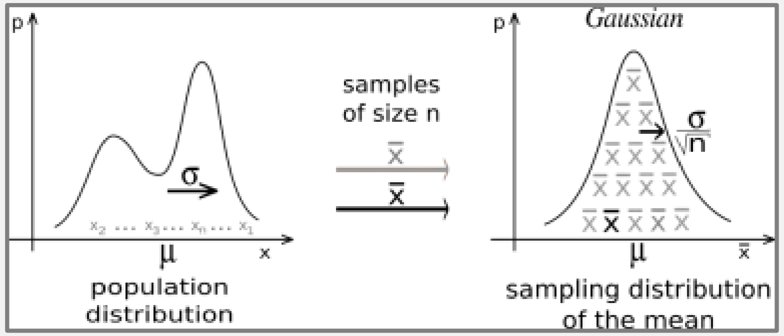
# PROBLEM DEFINITION



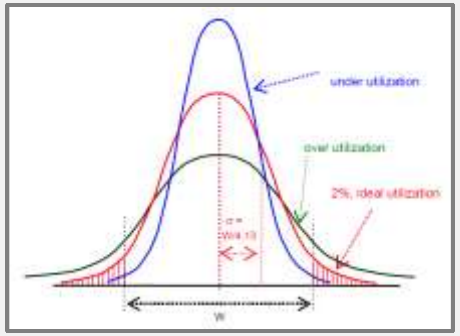

Finding the relationship between the task parameters and endpoint distribution

# HYPOTHESES

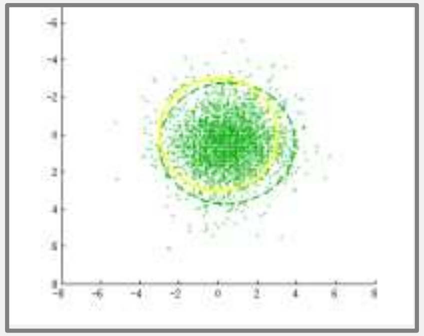
- **H1:** *The endpoint distribution in moving target selection is Gaussian.*
  - Control Limit Theorem
  - Endpoints of selecting static targets are modeled with Gaussian distributions in previous studies




[Control Limit Theorem from Rouaud 2013]



[Zhai etc. 2004]



[Bi & Zhai 2013]

# HYPOTHESES

- **H2:** *The initial distance A does not affect the endpoint distribution.*
  - The initial distance does not affect the endpoint distribution in static target selection
  - Initial distance showed little effect on movement time in moving target selection with position control system

$$X \sim N(\mu, \sigma)$$
$$\mu = 0$$
$$\sigma = W / \sqrt{2\pi e}$$

[Zhai etc. 2004]

$$X \sim N(\mu, \sigma)$$
$$\mu = c$$
$$\sigma = \sqrt{a + bW^2}$$

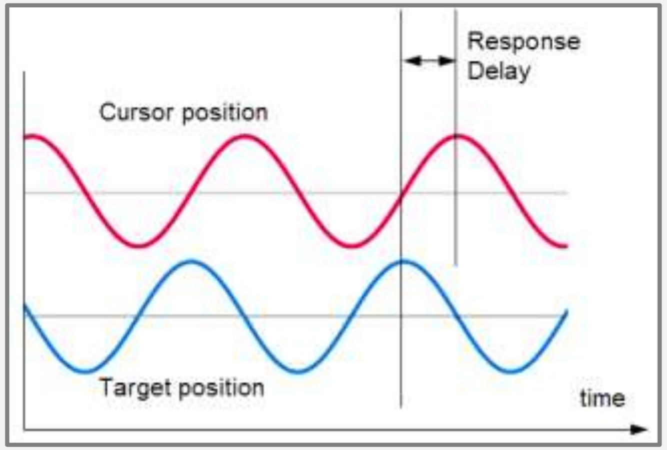
[Bi & Zhai 2013]

Position control system

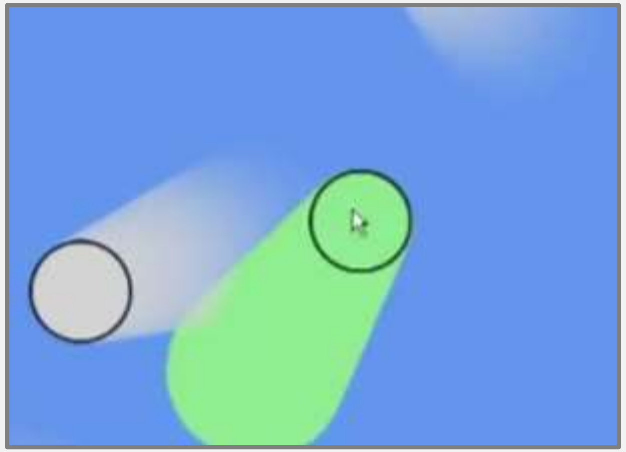
[Jagacinski & Balakrishnan 2002]

# HYPOTHESES

- **H3:** *The target width (W) and the moving velocity (V) affect the endpoint distribution.*
  - Standard deviation σ of endpoint distribution is usually assumed to be proportional to target size
  - Target movement leads to a larger fall-behind effect and distributed range of endpoints




[Pavlovych & Stuerzlinger 2011]

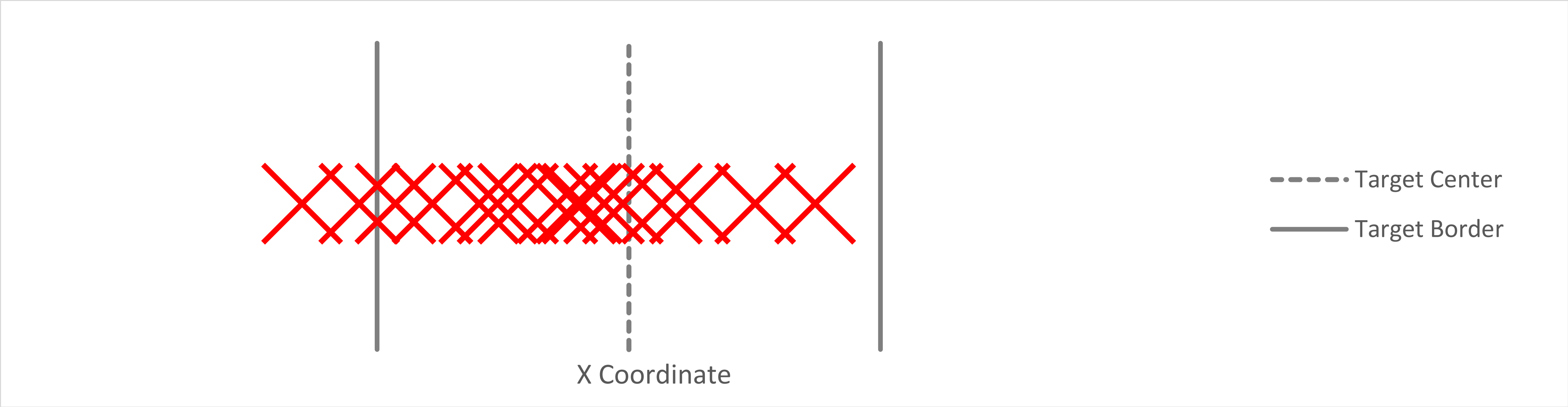


[Hasan etc. 2011]

# THEORETICAL DERIVATION

- Back to the problem:

**The relationship between task parameters and endpoint distribution**



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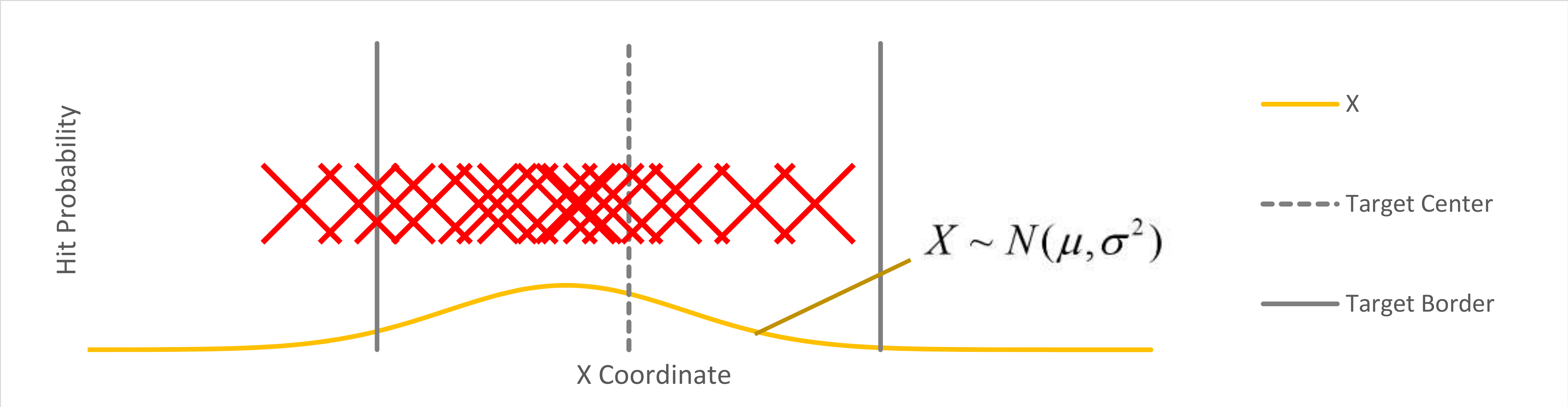
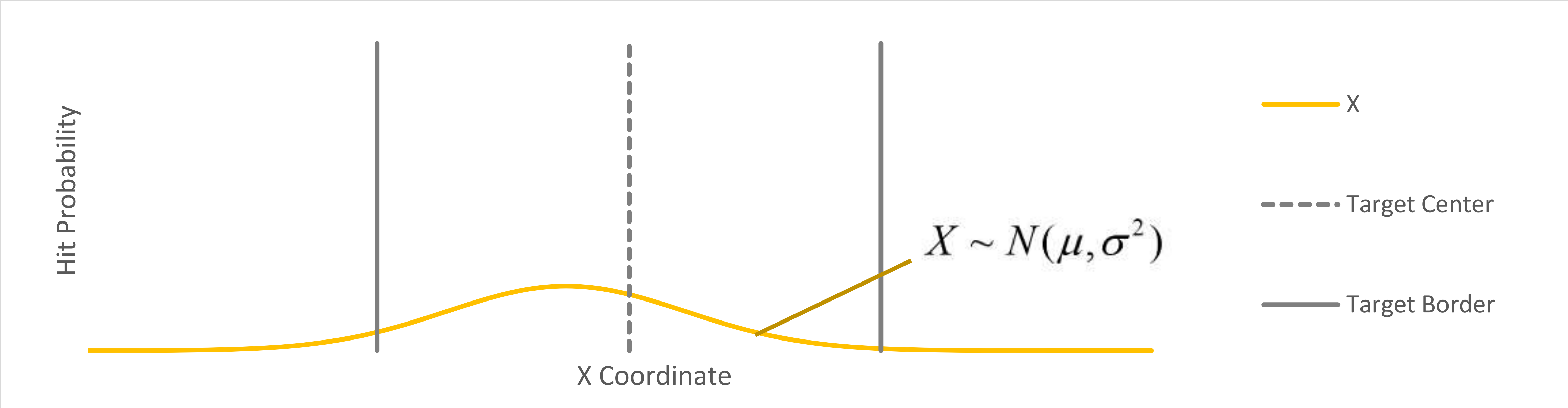



- From Hypothesis 1, the endpoint distribution can be formulated as a Gaussian distribution, and it can be uniquely defined by μ and σ of the Gaussian distribution.

# THEORETICAL DERIVATION

- Problem now is transmit to:

**Finding the function of $\mu = f(A, W, V)$ and $\sigma = g(A, W, V)$**



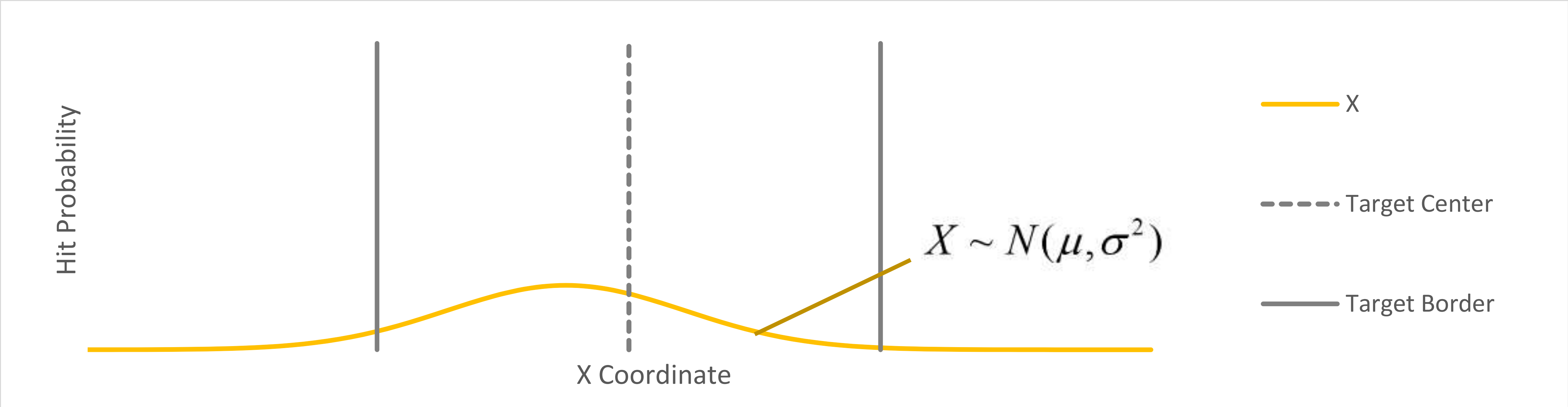

- From Hypothesis 2, the endpoint distribution is not related to A, so we can remove it from our target functions.

MODELING ENDPOINT DISTRIBUTION

# THEORETICAL DERIVATION

- Problem now is transmit to:

**Finding the function of μ = f(W, V) and σ = g(W, V)**




- From Hypothesis 3, we can inferred that the endpoint distribution may consist with two Gaussian components related to W and V

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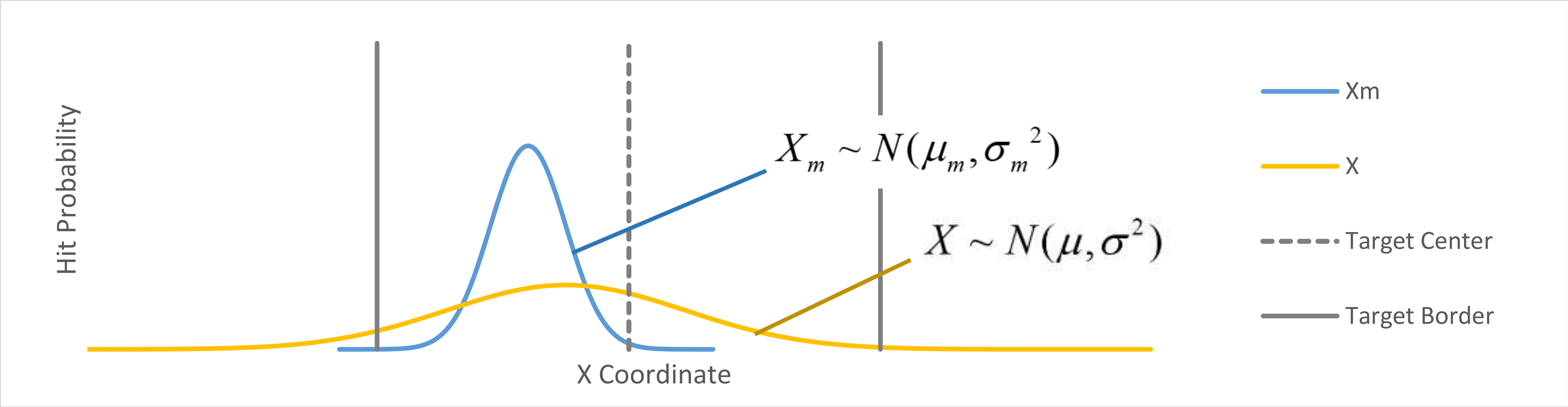


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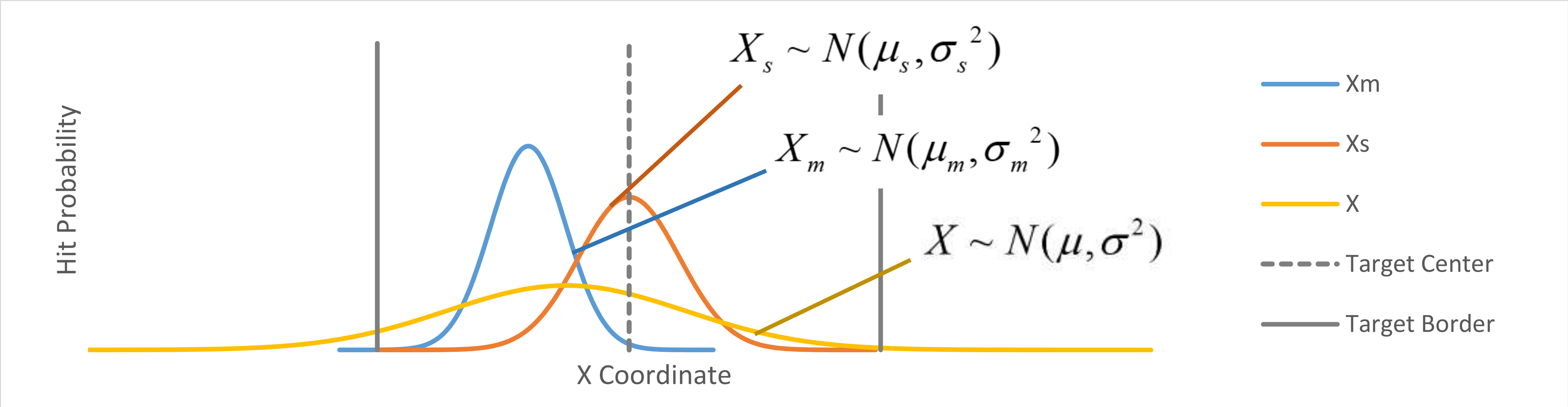


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# THEORETICAL DERIVATION

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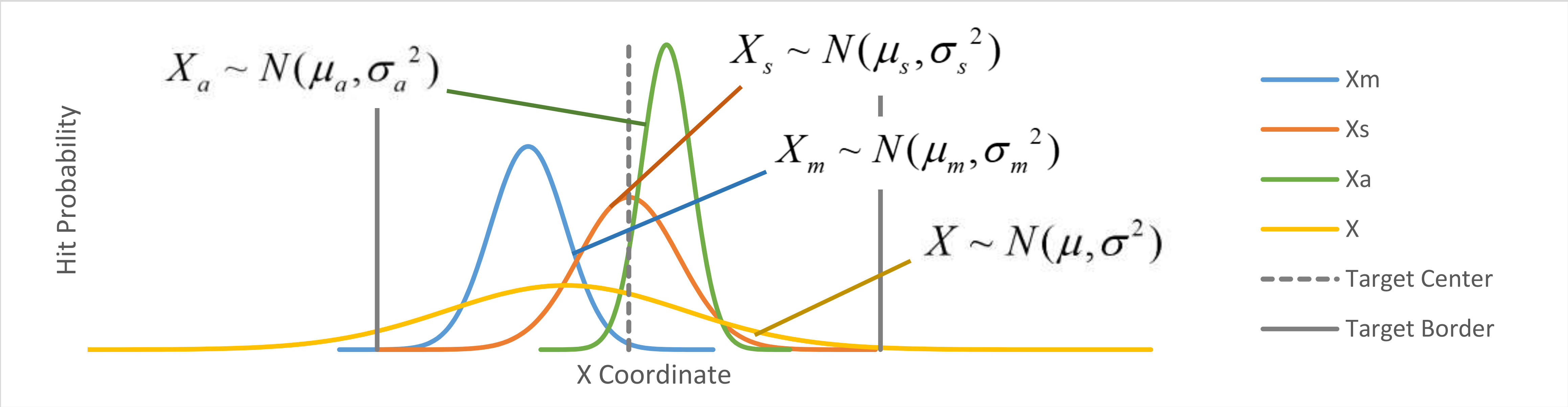
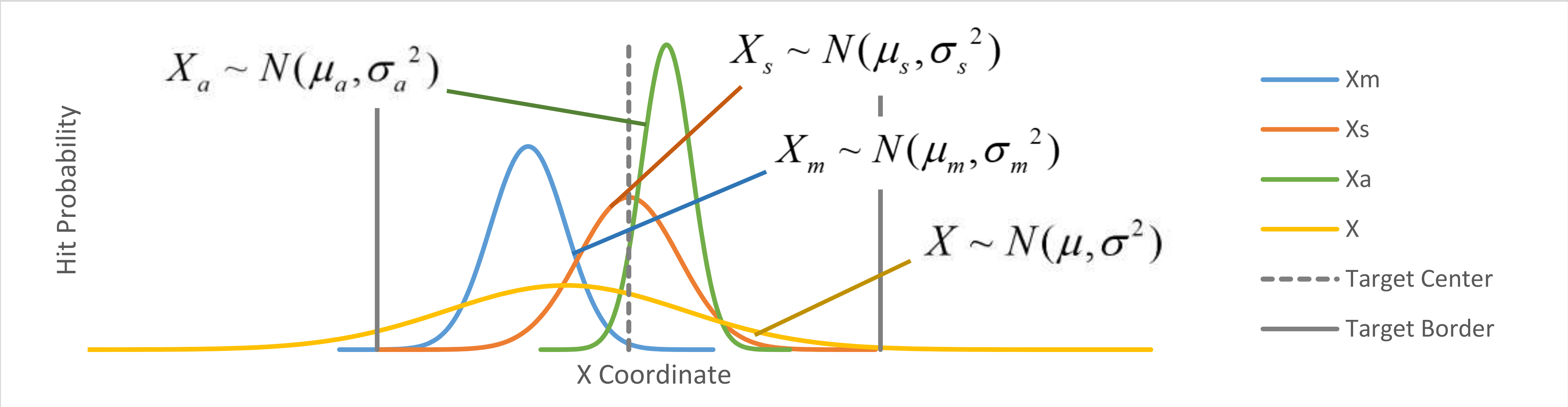


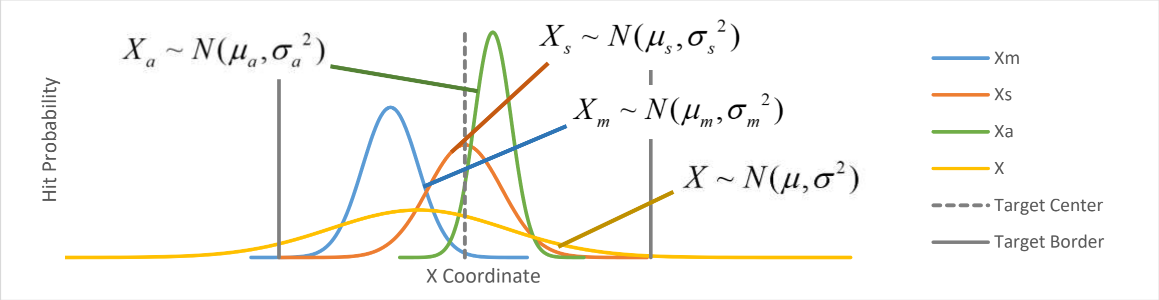

- We further add a third Gaussian component to reveal the absolute accuracy of device

# THEORETICAL DERIVATION




- By simply having the sum of these three Gaussian components, we can obtain the total Gaussian distribution and the formulations of μ and σ of this distribution

# THEORETICAL DERIVATION



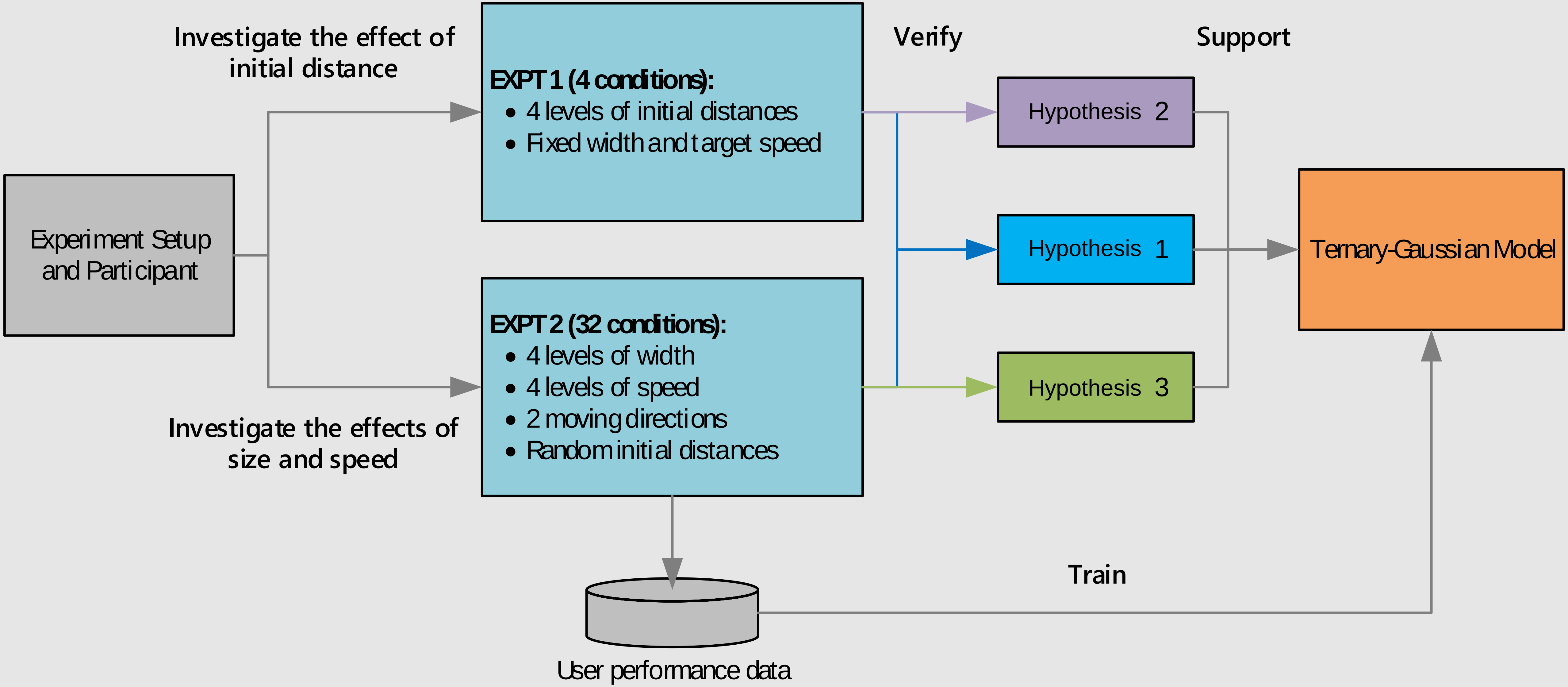

$$X = X_a + X_m + X_s \sim N(\mu, \sigma)$$

## Ternary-Gaussian model

$$\mu = \mu_a + \mu_m + \mu_s$$
$$= a + bV + cW$$
$$\sigma = \sqrt{\sigma_a^2 + \sigma_m^2 + \sigma_s^2 + \mathrm{cov}(X_m, X_s)}$$
$$= \sqrt{d + eV^2 + fW^2 + g\frac{V}{W}}$$

- We call the formulation of this total distribution the Ternary-Gaussian model.

# EXPERIMENT DESIGN



MODELING ENDPOINT DISTRIBUTION

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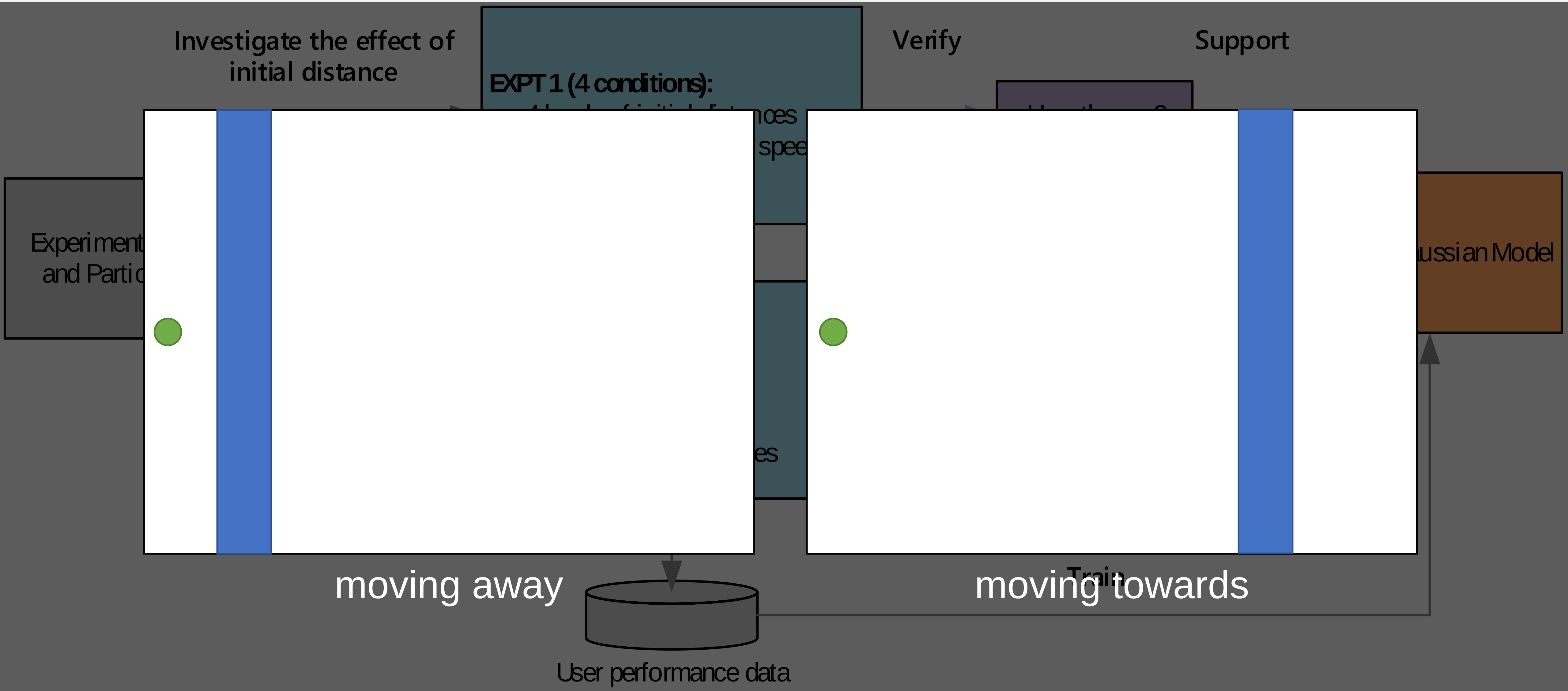

MODELING ENDPOINT DISTRIBUTION

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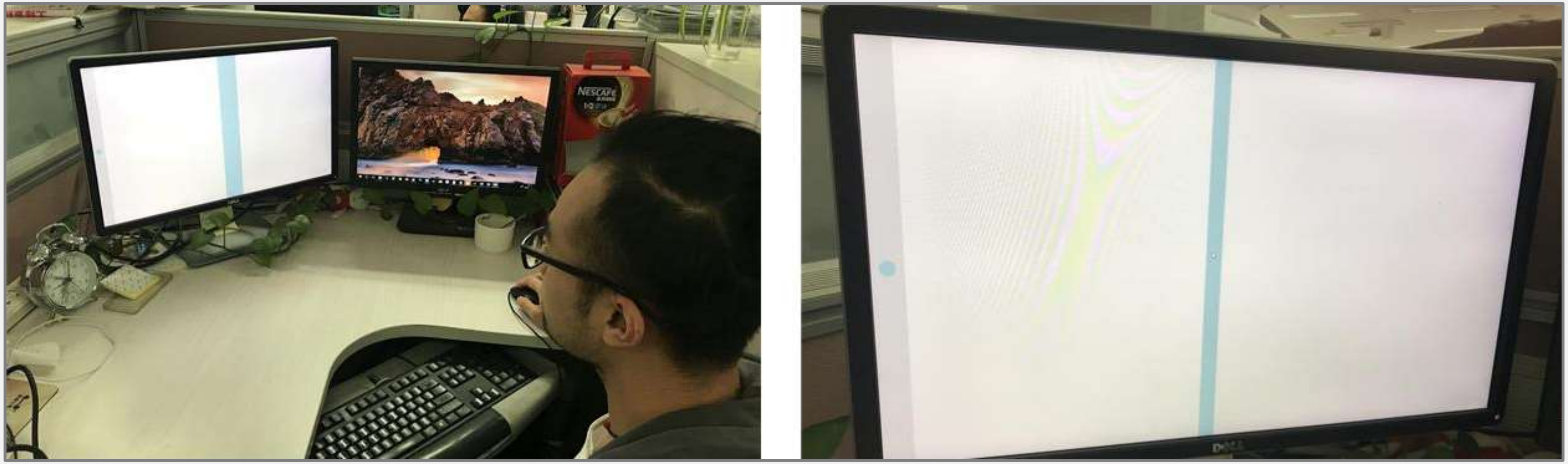
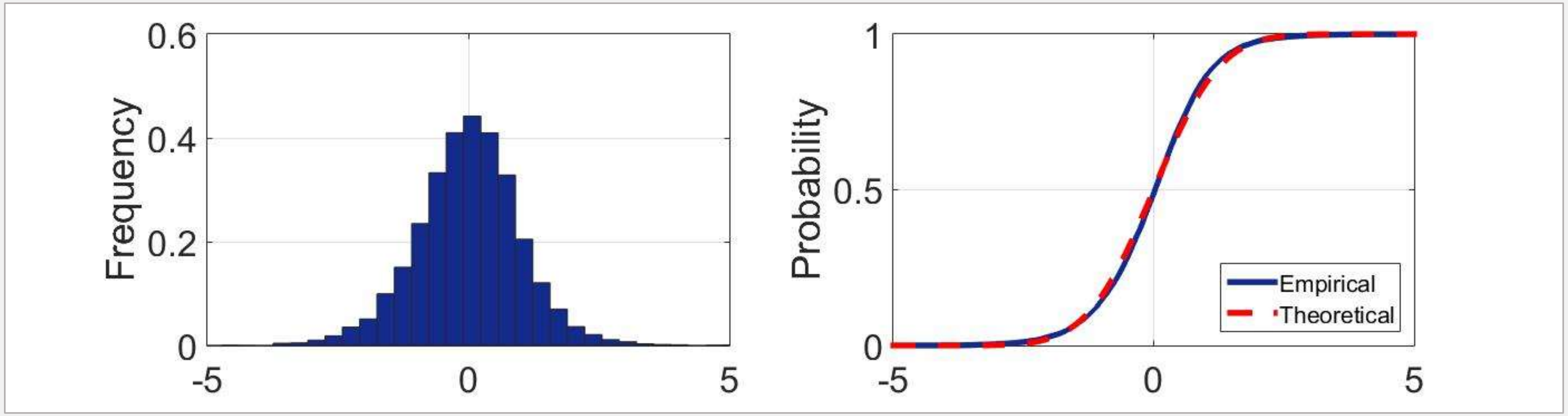


- 12 subjects (6 females and 6 males, with an average age of 27)
- 23-inch (533.2×312mm) LED display at 1,920×1,080 resolution
- Dell MS111 mouse with 1000 dpi as pointing device

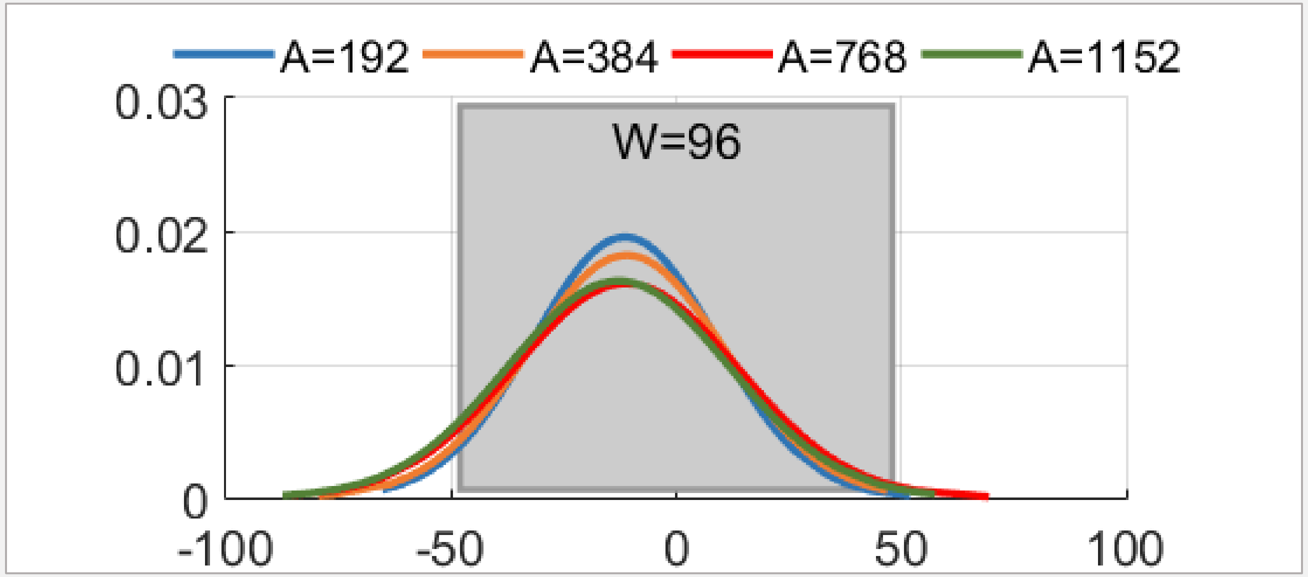
# HYPOTHESES VERIFICATION




All distributions of EXPT 1 and EXPT 2 passed the normality test.

**The endpoint distribution of moving target selection is Gaussian.**

# HYPOTHESES VERIFICATION

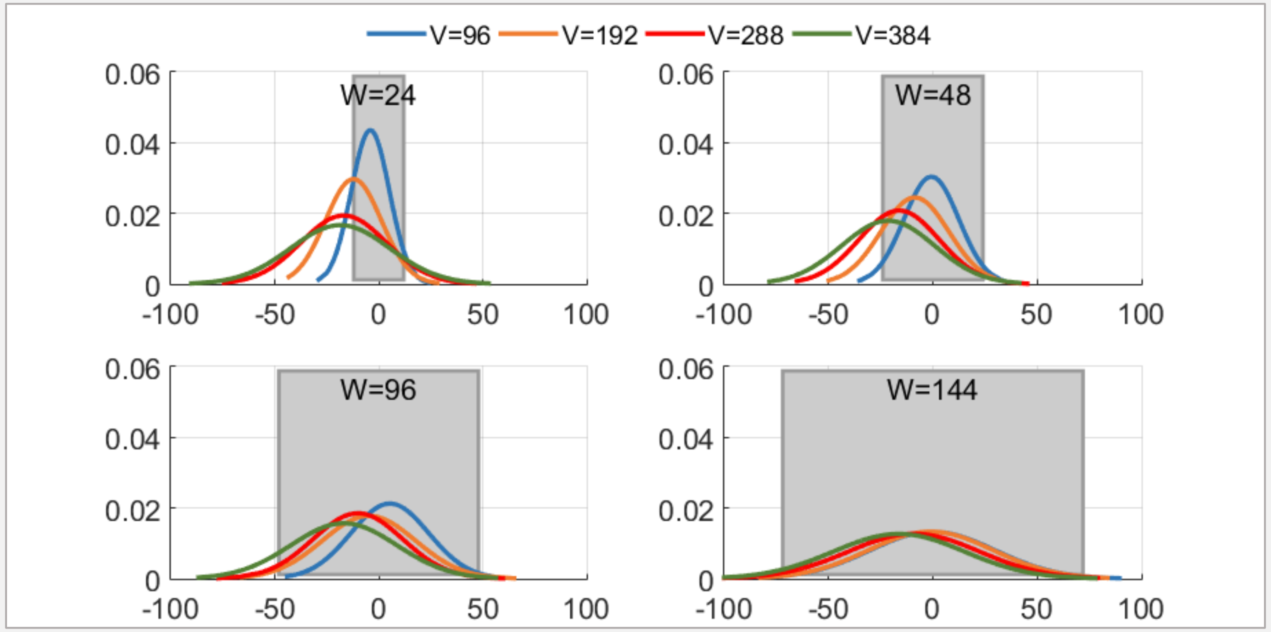



Both μ and σ of the endpoint distribution showed no significant different across all the 4 A levels.

**Initial distance A has little effect on the endpoint distribution.**

MODELING ENDPOINT DISTRIBUTION

# HYPOTHESES VERIFICATION

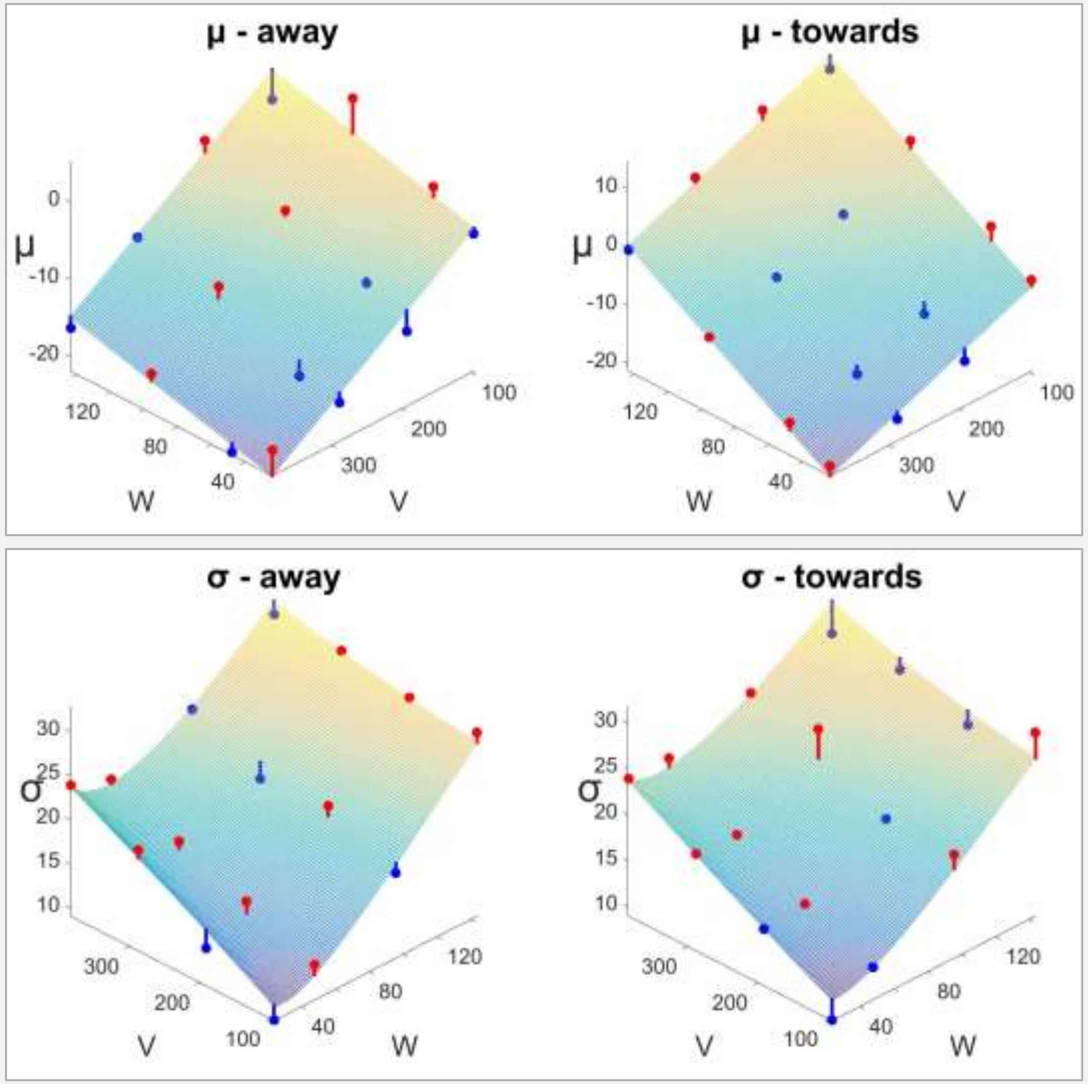



Both V and W exhibited significant effects on μ and σ, and their interaction effect is also significant.

**Target width and velocity significantly affect the endpoint distribution.**

# MODEL FITTING

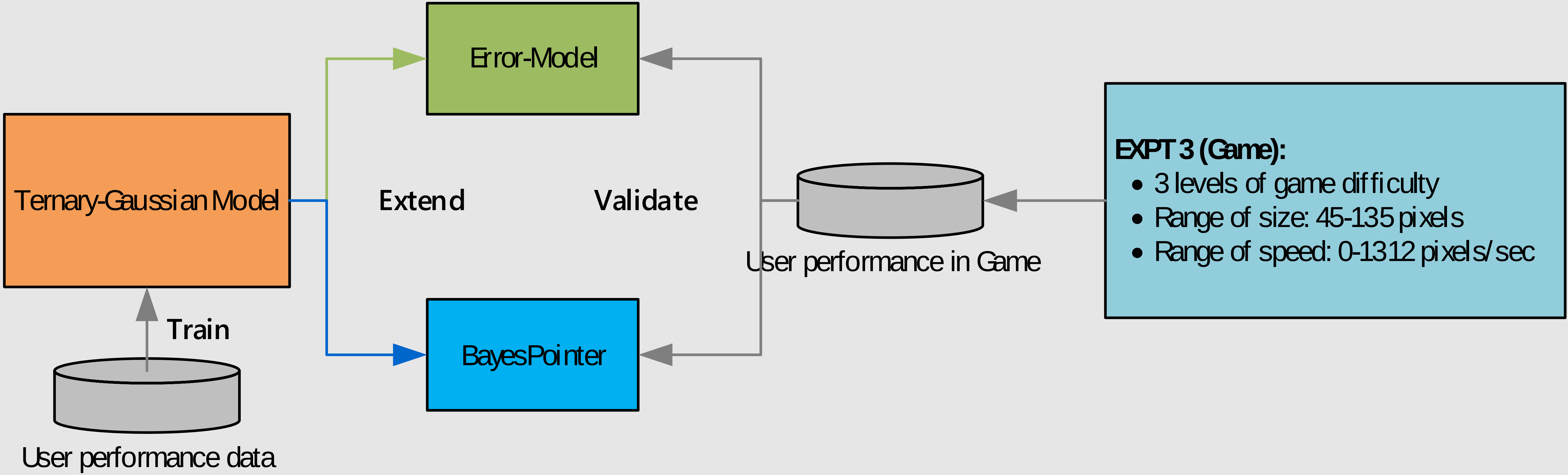
| parameters | $R^2$ | mean $R^2$ |
|---|---|---|
| μ-away | 0.926 | 0.952 |
| μ-towards | 0.978 | |
| σ-away | 0.97 | 0.946 |
| σ-towards | 0.923 | |



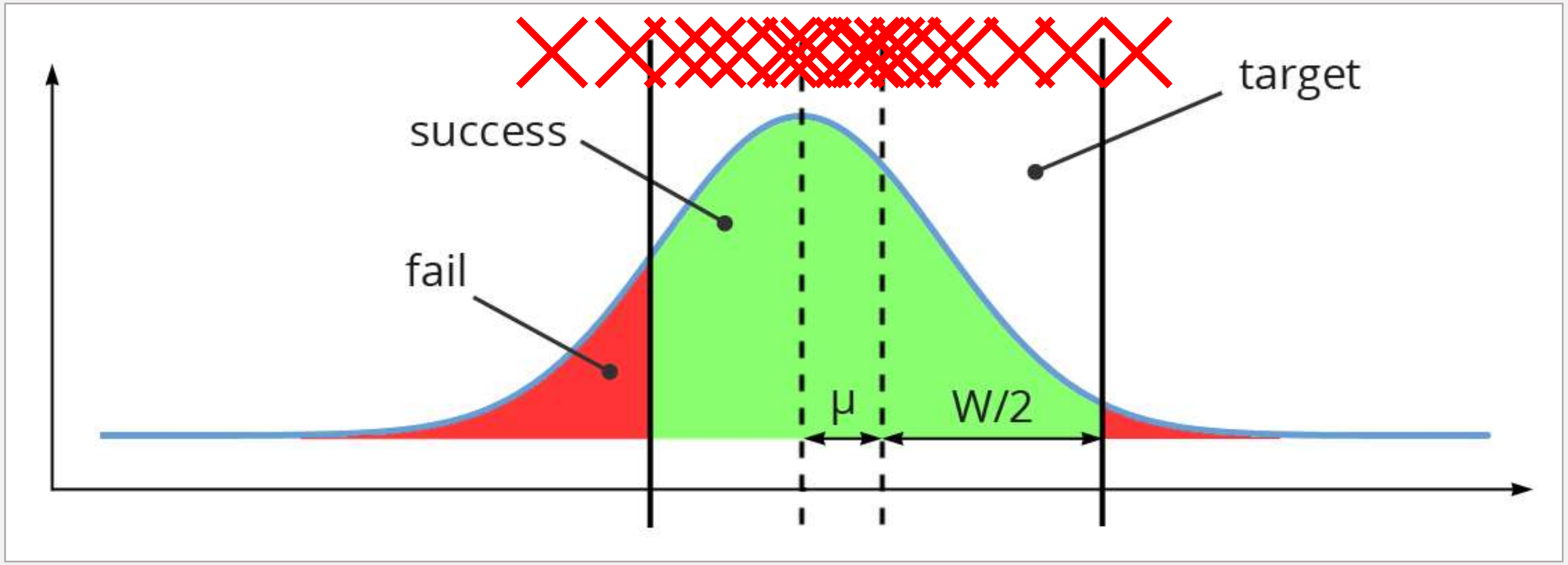

The model fits the data well for both μ and σ in the both moving directions

MODEL EXTENSIONS

# ERROR RATE PREDICTION AND TARGET SELECTION



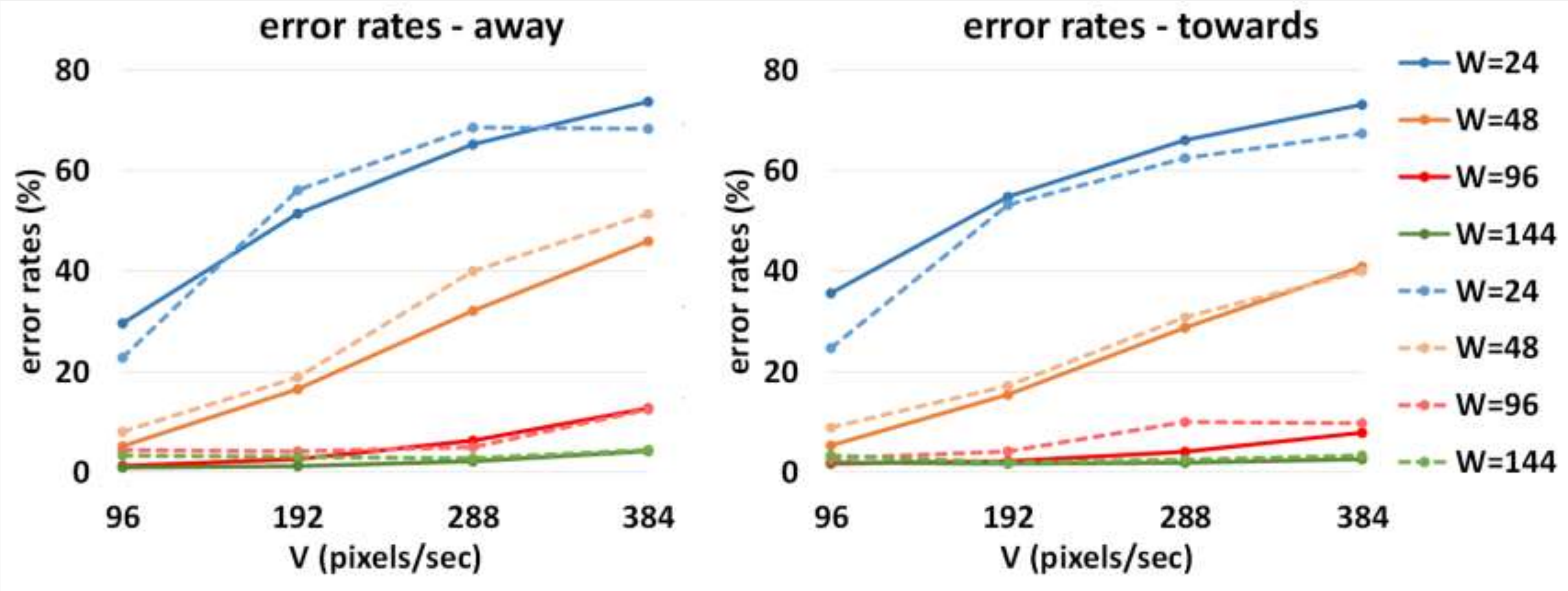
# ERROR-MODEL




- Error rate: the possibility of endpoint drop outside of a target.
- Calculate the area out of the target's boundaries through CDF (Cumulative distribution function) of the endpoint distribution.

## MODEL EXTENSIONS

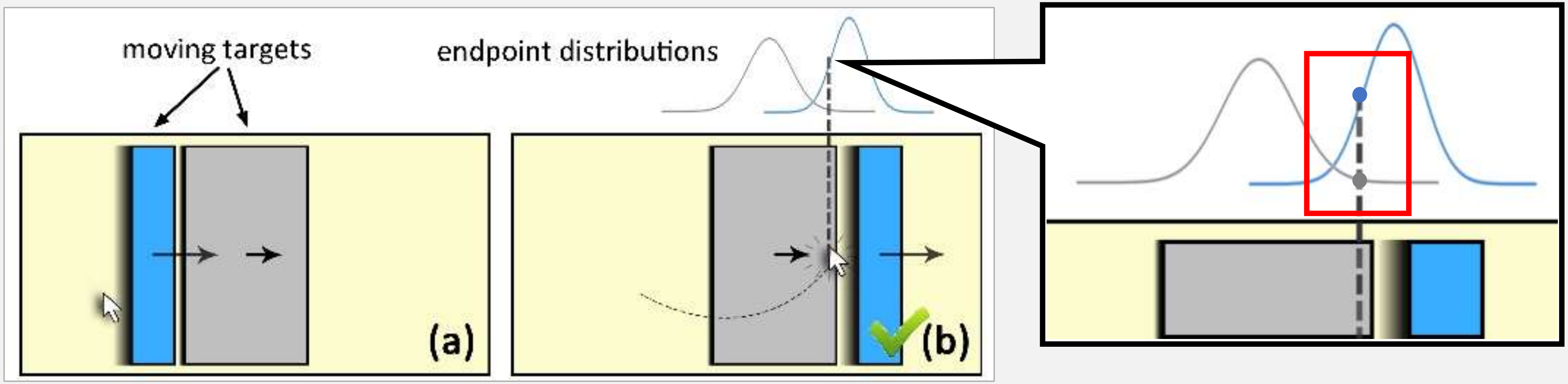
# ERROR-MODEL




- Error-Model fitted the data well in both moving directions
- Error rate increases when target velocity increases and when target width decreases

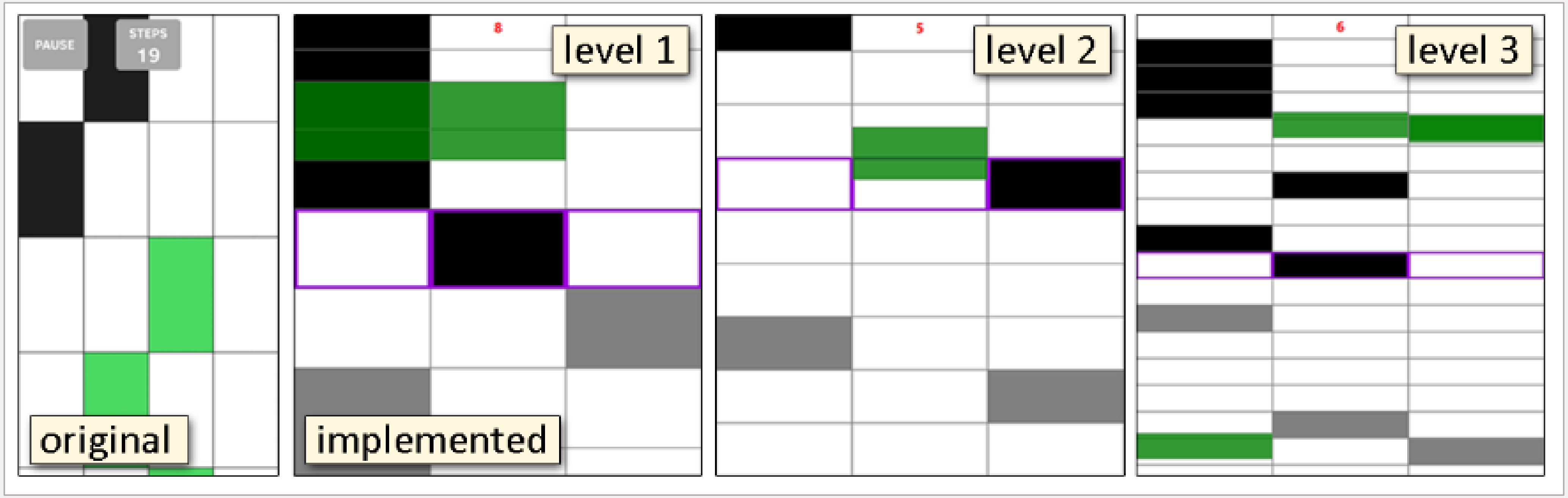
MODEL EXTENSIONS

# BAYESPOINTER




- BayesPointer integrates the Ternary-Gaussian model into Bayes' rule to determine the intended target instead of the physical boundaries.
- likelihood function (Blue) > likelihood function (Gray)

# EVALUATION IN A GAME INTERFACE



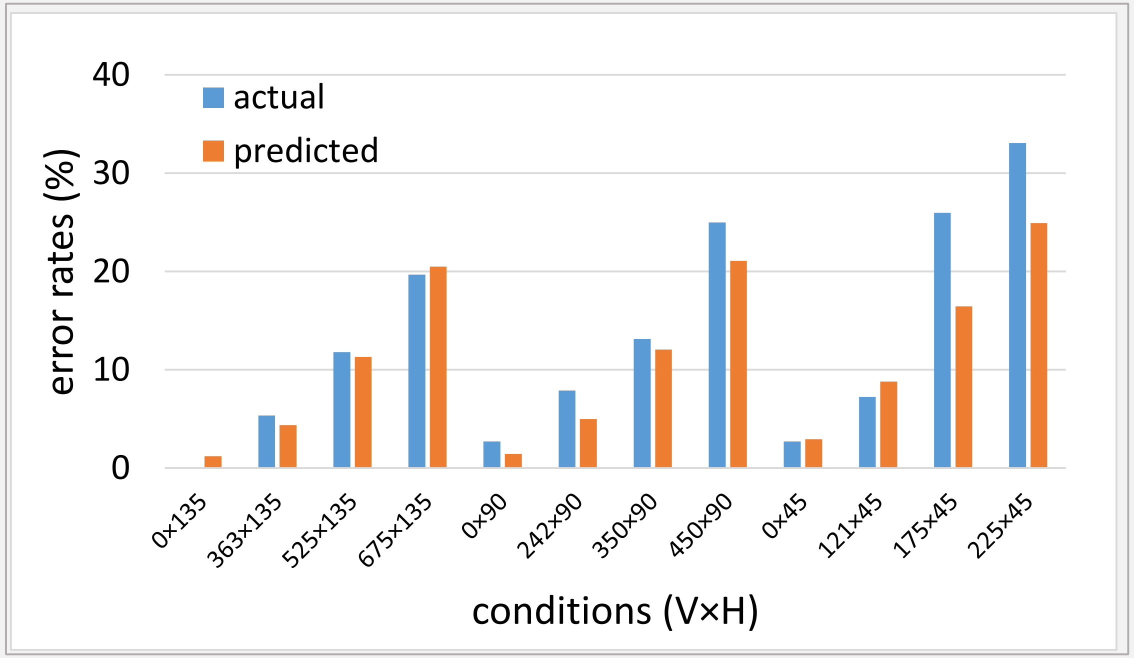

The popular game "Don't Touch The White Tile" in iOS App Store

Players had to tap the black tile in the lowest row

3 game levels with decreased target size, 5 lives for each level

MODEL EVALUATION

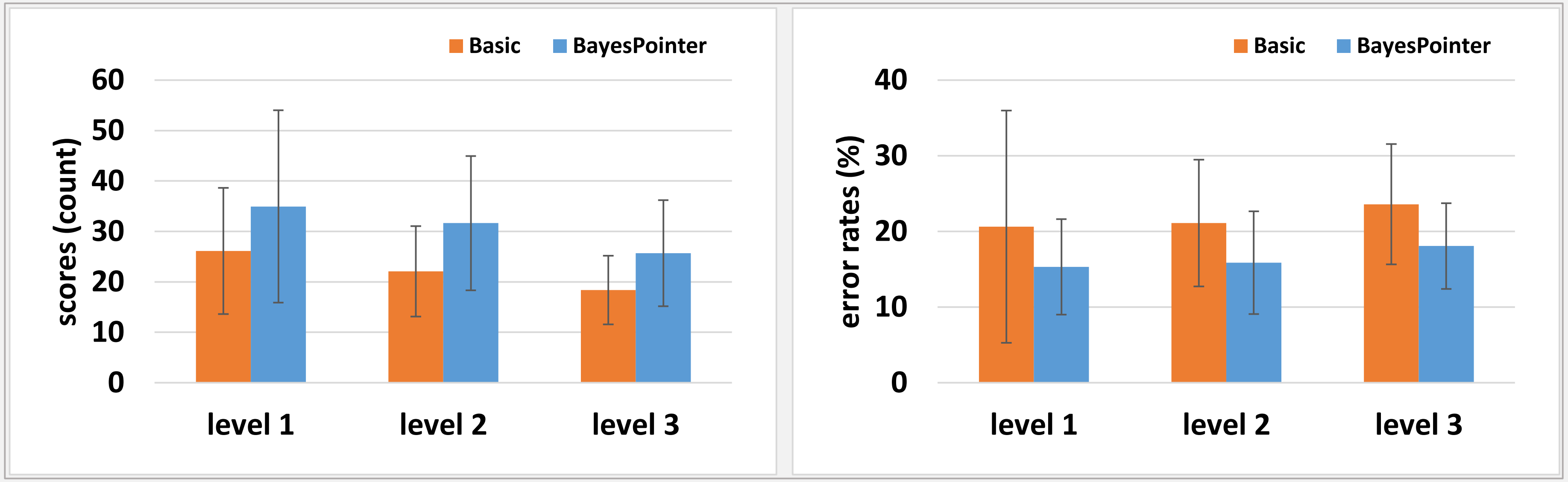
# PREDICTING ERROR RATE




Error-Model showed good performances in predicting error rate in almost all conditions (average MAE of 2.7%).

MODEL EVALUATION

# ASSISTING THE SELECTION OF MOVING TARGET




BayesPointer showed higher selection accuracy compare to Basic technique

Subjective feedback showed that participants like using BayesPointer more than using Basic technique

# CONCLUSIONS

- The first attempts to model human behavior uncertainty in moving target selection
- A Ternary-Gaussian model is proposed to interpret the endpoints distribution in moving target selection
- Two model extensions were demonstrated include predicting error rates and assisting moving target selection

# TAKEAWAYS

- Initial distance does not affect the endpoint distribution in moving target selection

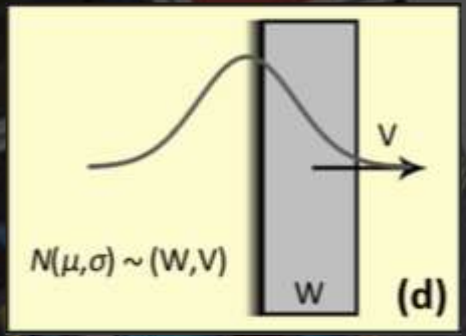
- When the target is moving fast the endpoints tend to drop behind the target and have a larger distributed range

- Error rate increases when target velocity increases and when target width decreases

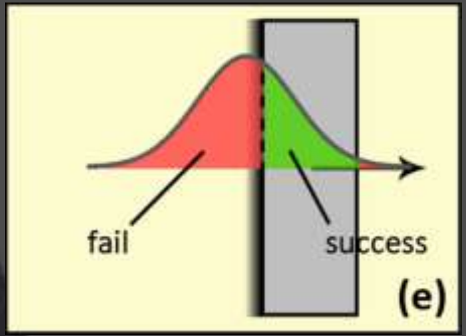
# FUTURE WORK

- Examining whether our model can be transferred into other interaction devices such as touch screen and stylus
- Modeling uncertainty in selecting moving targets with changing velocity and in 2D/3D space
- Comparing BayesPointer with other state-of-the-art pointing techniques such as Bubble Cursor and Comet

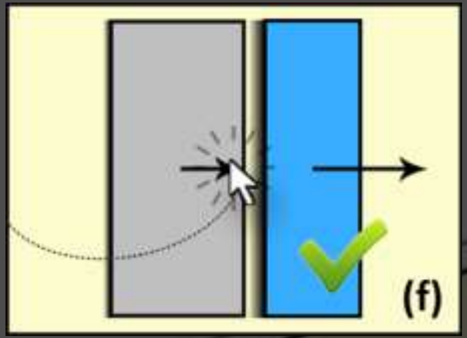
# Q & A:




Ternary-Gaussian Model




Error-Model




BayesPointer

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