

# g-RIPS 2022 Mitsubishi Project B Final Presentation

Justin Lien, Ariana Brown, Lee Fisher, Fumiya Okazaki

Multi-Objective Optimization for Best Early Prediction of Extreme Weather Events

**Academic Mentor:** Dr. Hiroyasu Ando

**Industry Mentors:** Dr. Yusuke Ito and Dr. Hidenobu Tsuji

August 9, 2022

## 1 Introduction

Motivation for the Project  
Project Objective

## 2 Shape-Packing Model

Mathematical Setup  
The 2-D Case Study and Circle Packing  
The 3-D Case and Shape Packing  
Tokyo Case Study

## 3 SVD Model

New Strategy: reconsidering the significance function  
Dr. Nonomura's Method  
Japan Case Study  
Looking at Tokyo Again

## 4 Conclusion & Reference

Conclusion  
Reference



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Water vapor and wind ) Cumulonimbus clouds

) Heavy rain ) Extreme weather event

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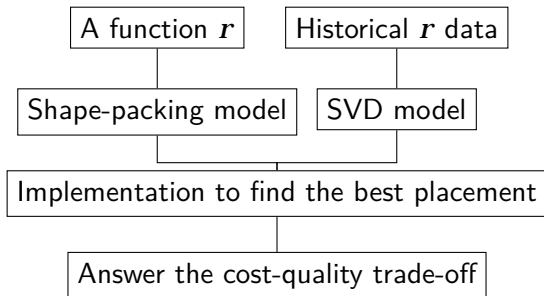
For this project, we will consider the best placement of high-grade and low-grade LiDAR instruments in Japan to help sense extreme weather.

**Figure:** Cumulonimbus Clouds and LiDAR Instruments



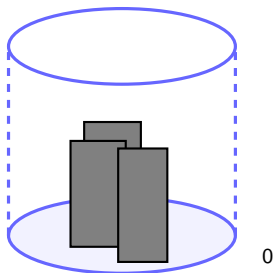
**GOAL:** To solve a multi-objective optimization problem regarding the performance of placement and cost of the instruments.

**Strategy:** Depending on the type of data for significance function  $r$ , to accomplish this we will:



## Definition

The **prediction area**  $\Omega$  is a bounded finite, real, 2 dimensional manifold (the topography of a city). The **prediction space**  $\mathcal{P} = \Omega \times (0; \infty)$  where  $\infty > 0$  can be infinite. This is understood to be the surface of a city and the air space of interest above the surface of the ground.



**Figure:** The prediction space and the prediction area.

## Definition (Water and Wind Significance)

The functions  $r_w; r_f: [z_0; z_1] \rightarrow \mathbb{R}^+$ , where  $[z_0; z_1]$  is an interval of time where an extreme weather event would occur.



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Large  $r_{..}$  or  $r_f$ ) Extreme weather events are more likely.

$$r(\mathbf{x}; \cdot; z) = r_{..}(\mathbf{x}; \cdot; z) + r_f(\mathbf{x}; \cdot; z) \quad (1)$$

The sum is simply **significance function**.

## Definition

The **viewing set** of an instrument,  $\mathcal{V}_i(\mathbf{x}; \mathcal{I}_i)$ , is a subset of  $\mathcal{I}_i$  which depends on the placement,  $\mathbf{x}$  and the type  $\mathcal{I}_i$ .

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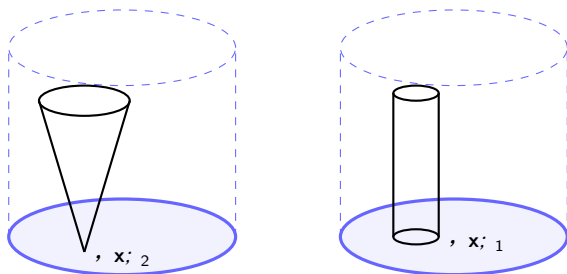
There are two types of LiDAR instruments: low-grade and high-grade.

- Low-grade ) Cost & Viewing set &
- High-grade ) Cost & Viewing set %

Assuming uniform continuity of the significance function, let the cheaper instrument be a thin vertical cylinder where the reading is constant for each height section with controllable error.

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We will let the viewing set of the expensive instrument to be a wider conical set with viewing angle  $\theta$ .



**Figure:** Viewing sets for high and low quality instruments.

## Definition

A **configuration**  $\lambda$  of  $n$  instruments is a set of  $n$  pairs,  $(\mathbf{x}_1; \tau_1); \dots; (\mathbf{x}_n; \tau_n)$  that represent the placements and types of instruments. The viewing set of  $\lambda$  is the union of the viewing sets of each of the instruments.

$$\mathcal{V}(\lambda) = \bigcup_{s=1}^n \mathcal{V}_s(\mathbf{x}_s; \tau_s) \quad (2)$$

$$k(\lambda) = \sum_{z \in \mathcal{Z}} r(\mathbf{x}; \tau; z) \quad (3)$$

$$; (\lambda) = \sum_{s=1}^n ; (\tau_s) \quad (4)$$

Our strategy to find a good value configuration is broadly the following:

**1 Construct the significance function**

Climate data, topography data )

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## ② Find the best placement of each configuration

Input: a fixed  $f, g$  (Numerical Model)    Output: the best placement  $f, x, g$

Our strategy to find a good value configuration is broadly the following:

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Climate data, topography data )

identify the significant region for the cumulonimbus clouds formation

### 2 Find the best placement of each configuration

Input: a fixed  $f, g$  (Numerical Model)    Output: the best placement  $f, g$

### 3 Find optimizers: We will select a Pareto efficient compromise between cost and quality.

To simplify the problem, we only consider the significant function with the following form:

$$r = e(\mathbf{x})L(\langle \cdot \rangle)H(\mathbb{Z}) \quad (5)$$

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$e(\mathbf{x})$ : information on the population and topography.

$L(\langle \rangle)$ : meteorological information about what altitudes are important to observe for predicting an extreme rainfall event.



h?2 k@. \* b2 aim/v M/ \*B`+H2 S +FBM;

hQ bBKTHB7v i?2 T`Q#H2K- r2 QMHv +QMbB/2`  
7QHHQrBM; 7Q`K,

$$a = \tau(t); (\lambda \tau_i) \quad U8V$$

$\tau(t)$ , BM7Q`K iBQM QM i?2 TQTmH iBQM M/ i  
;( $\lambda$ ), K2i2Q`QHq;B+ H BM7Q`K iBQM #Qmi r1  
iQ Q#b2`p2 7Q`T`2/B+iBM; M 2ti`2K2` BM7  
 $\tau_i$ ), /2b+`BTiBQM Q7 /Bm`M H M/ b2 bQM H













h?2 k@. \* b2 aim/v M/ \*B`+H2 S +FBM;

LQr- r2 K JP2\_1 bbmKTiBQMb

6Q` ?B;? [m HBiv BMBb M Q Ki2QMQ-rB/2X

;(x y i HQr M/ ?B;? HiBim/2bX

h?2 ?B;? [m HBiv BMbi`mK2Mi + M #2 TT`Qt

$$O_{t_k} = (t; \backslash) R^+$$

UeV

$$O_{t_R} = (t; \backslash) R^+$$

UdV

r?2`Bb i?2` /Bmb Q7 i?2 +B`+mH `b2+iBQI

6`QKeWr2 + M bBKTHB7v i?2 pB2rBM; b2i b 7

$$O_M = \begin{bmatrix} M \\ O_{t_B} \end{bmatrix} \quad O_M = R^+$$

$$\begin{bmatrix} M \\ (t_B \backslash) \end{bmatrix}$$

$$Z_{iR}^B$$

Z

B R

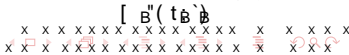
Z

$$Z(M) =$$

$$i_y [B(t_B \backslash) R^+$$

$$T(t); (x \backslash) / x t / i = E$$

$$T(t) / t$$



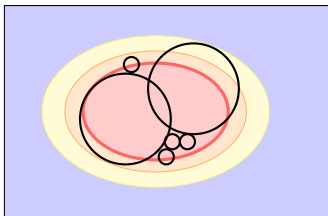


h?2 k@. \* b2 aim/v M/ \*B`+H2 S +FBM;

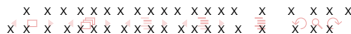
PTiBKBZBM+ M #2 mM/2`biQQ/ b +B`+H2 T

$$\sum (t_R :: t_M \cdot R :: M) = \frac{T(t)}{t} [B'(t_B)]$$

U3V



6B;m`M,2t KTH2 7mM+BBQM #v ?2 iK T- M/ +?QB  
+QM};m` iBQMX \_2//2` +QHQ`b +Q``2bTQM/ iQ ?B;?









h?2 k@. \* b2 aim/v M/ \*B`+H2 S +FBM;

h?2 :`22/v H;Q`Bi?K

h?Bb TT`Q +? Bb bi M/ `/ K2i?Q/ 7Q` b2Mb  
; BM- BMbi2 / Q7 i`vBM; HH TQbbB#H2 TH

SH +2 H `;2` +B`+H2 S Q M 2 #K Q M H 2 ` +B` +H

AM Qm` 2tT2`BK2Mib- r2 7QmM/

:`22 /v "B b2 /MB7Q` :K /B2Mi .2b+2Mi

G i2` - r2 rBHH BKTH2K2Mi i?2 ;`22/v H;Q`B





h?2 j@. \* b2 M/ a? T2 S +FBM;

h?2 j .BK2MbBQM H \* b2

q2 M22/ H2bb bbmKTiBQMb M/ TT`QtBK iBQM

$$\begin{aligned}
 O_M &= [^M O_{t_B B} \\
 Z_M &= Z_{i_R}^B Z Z \quad a(t; \lambda(\tau)) / x t / i \\
 &= \int_S O_{t_B B} \quad a(t; \lambda) / x t
 \end{aligned}$$





h?2 j@. \* b2 M/ a? T2 S +FBM;

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 &= \int_{i_R} Z Z \quad O_{t_B B} \\
 &= \int_{i_R} S \quad a(t; \lambda) / x t \\
 & \quad O_{t_B B}
 \end{aligned}$$

JQbi Q7 i?2 b K2 H;Q`Bi?Kb M/ bi` i2;B2b -  
k. iQ i?2 j. + b2X







h?2 j@. \* b2 M/ a? T2 S +FBM;

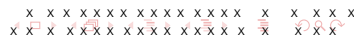
h?2 j .BK2MbBQM H \* b2

q2 M22/ H2bb bbmKtiBQMb M/ TT`QtBK iBQM

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 Z^R_{i_R} Z Z \\
 Z(M) &= S \quad a(t; \lambda(i)/x\lambda/i \\
 &= \int_{i_R} Z Z \quad O_{t_B B} \\
 &= \int_S \quad a(t; \lambda/x\lambda \\
 &\quad O_{t_B B}
 \end{aligned}$$

JQbi Q7 i?2 b K2 H;Q`Bi?Kb M/ bi` i2;B2b -  
k. iQ i?2 j. + b2X

h?2 K BM T`BM+BTH2b M/ +Q/2 7Q` i?2 k. M















bB;MB}+ M+2 7mM+iBQM 7Q` hQFvQ

q2 mb2/ ` BM7 HH / RiQ`QKTK

JQ`2 ?2 pv ` BM7 HH BM+B/2M+2b `2+2Bp2/

\*QmMi i?2 MmK#2` Q7 ?2 pv ` BM 2p2M

) AMi2`TQH i2 iQ 2ti2M/ #2vQM/ / i b

) LQ`K HBx2 bXiX i?2 K tBKmK Bb R





hQFvQ \* b2 aim/v

bB;MB}+ M+2 7mM+iBQM 7Q` hQFvQ

q2 mb2/ ` BM7 HH / RiQ`QKTK

JQ`2 ?2 pv ` BM7 HH BM+B/2M+2b `2+2Bp2/

\*QmMi i?2 MmK#2` Q7 ?2 pv ` BM 2p2M

) AMi2`TQH i2 iQ 2ti2M/ #2vQM/ / i b

) LQ`K HBx2 bXiX i?2 K tBKmK Bb R

.QMöi TH +2 b2MbQ`b Qp2` i?2 Q+2 M5







hQFvQ \* b2 aim/v

bB;MB}+ M+2 7mM+iBQM 7Q` hQFvQ

q2 mb2/ ` BM7 HH / RiQ`QK

JQ`2 ?2 pv ` BM7 HH BM+B/2M+2b `2+2Bp2/

\*QmMi i?2 MmK#2` Q7 ?2 pv ` BM 2p2M

) AMi2`TQH i2 iQ 2ti2M/ #2vQM/ / i b

) LQ`K HBx2 bXiX i?2 K tBKmK Bb R

.QMöi TH +2 b2MbQ`b Qp2` i?2 Q+2 M5

q2 mb2/ i?2 :`22/v H;Q`Bi?K iQ TH +2 R9 b2







AMi`Q/m+iBQM

a? T2@S +FBM; JQ/2H

ao. JQ/2H

\*QM+HmbBQM

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L2r ai` i2;v, `2+QMbB/2`BM; i?2 bB;MB}+ M+2 7mM+iBQM

#Qmi aB;MB}+ M+2 6mM+iBQM

a(t; x i) T`2/B+ib M 2ti`2K2 r2 i?2` 2p2Mi #270

i?2 \*mK mHQMBK#mbX

Ai + M #2 TT`QtBK i2/ #v bQK2 7mM+iBQM C

}2H/

$$a(t; x i) = \alpha(\rho(t; x i); f(t; x i))$$

h?2 b2MbQ`lpbMkT H2B+? Bb 2[mBp H2AKi iQ b

<sup>k</sup> +im HHv- Bi HbQ /2T2M/b QM i?2 +?2KB+ H +QKTQM2  
Qp2`@b im` iBQM +QM/BiBQM- 2i+X



L2r ai` i2;v, `2+QMbB/2`BM; i?2 bB;MB}+ M+2 7mM+iBQM

#Qmi aB;MB}+ M+2 6mM+iBQM

a(t; x i) T`2/B+ib M 2ti`2K2 r2 i?2` 2p2Mi #270  
i?2 \*mK mHQ MBK#mbX

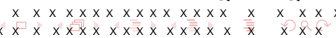
Ai + M #2 TT`QtBK i2/ #v bQK2 7mM+iBQM C  
}2H/

$$a(t; x i) = \alpha(\rho(t; x i); f(t; x i))$$

h?2 b2MbQ`lpbMkT H2B+? Bb 2[mBp H2AKi iQ b  
h?2`2 `2 irQ T`Q#H2Kb,

q2 /Q MQi FMQR i?2 iKQbT?2`B+ b+B2M+2 iC  
q2 /Q MQi ? p2 ++2bb iQ ;QpQM/#X b2ib Q7

<sup>k</sup> +im HHv- Bi HbQ /2T2M/b QM i?2 +?2KB+ H +QKTQM2  
Qp2`@b im` iBQM +QM/BiBQM- 2i+X





















.`X LQMqKm` öb J2i?Q/

q2 `2+QMbi`m+i i?2 i2KT2` im`2 }2H/ #v i?2

$$\mathfrak{S}_i = I \cdot * R_{V_i}$$

q?2MBb MQi b[m `2- i?2 BMp2`b2 Bb BM i?2  
h?2 2``Q` BM i?2 TT`QtBK iBQM Bb,

$$\mathfrak{S}_i \quad s_i = I \cdot * R_{>}$$

h?2 bBx2 Q7 i?2 2``Q` p2+i\*Q<sup>R</sup>XrBHH /2T2M/ Q  
A7 i?2 /2i2`KBM Mi Bb H `;2- i?2M i?2 2``Q`





.`X LQMqKm` öb J2i?Q/

hQ QTIBKBx2 Qm` TH +2K2M<sup>9</sup>- r2 b?QmH/ +Q

$$\max / 2(i^*) \quad Q \min / 2(i^* \quad R)$$

SH +BM; b2Mb~~Q~~:b~~B~~iK2BM2bbi? i i?2 \*Q~~B~~H~~Q~~7# 2  
R::: BQT`X

q2 mb2 i?2 :`22/v H;Q`Bi?K M/ a+?m` @+QK  
QT`r?B+? BM/2(i2) b~~Q~~Km+? b TQbbB#H2X

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$$9^* = ( \quad * \quad R ) \quad R$$











C T M \* b2 aim/v

h2KT2` im`2 K i`Bt 7Q` C T M

q2 mb2/ i?2 i2KT2` im`2 / i UkyikQV`Z` Q2ki C2  
K i`BtX

h?Bb bi` i2;v Bb mb2/ iQ `2 / i2KT2` im`2- #r  
`2 / i?2 bB;MB}+ M+2 7mM+iBQMX

PM i?2 b+ H2 Q7 i?2 2MiBL P K JT\* M / B 2 2 2 2 MB+  
#2ir22M G:a M/ >:aX

<sup>8</sup>C T M J2i2Q`QHq;B+ H ;2M+v





C T M \* b2 aim/v

h2KT2` im`2 K i`Bt 7Q` C T M

q2 mb2/ i?2 i2KT2` im`2 / i UkyikR V` 2` Q2ki C2  
K i`BtX

h?Bb bi` i2;v Bb mb2/ iQ `2 / i2KT2` im`2- #r  
`2 / i?2 bB;MB}+ M+2 7mM+iBQMX

PM i?2 b+ H2 Q7 i?2 2MiBL P K JT\* M / B 2 2 2 2 MB+  
#2ir22M G:a M/ >:aX

q2 mb2/ .`X LQMqKm` öb TT`Q +? iQ TH +2  
`QmM/ C T MX











h2KT2` im`2 K i`Bt 7Q` hQFvQ

q2 mb2/ i?2 i2KT2` im`2 / i UKyQR+V z`iQR?CJ  
K i`BtX

PM i?2 hQFvQ +Biv b+GH\_2: 1?Bz2`BEM+2 #2ir22  
M/ HQR ;` /2 b2MbQ`bX

h?2 ?B;? ;` /2 b2MbQ`b + M b22 K Mv HQ+ iE  
T`Q}H2b Q7 /D +2Mi bBi2b `2 M2 `Hv HBM2















GQQFBM; i hQFvQ ; BM

>Qr ;QQ/ Bb ;QQ/ b2MbQ`\

A7 >:a ? b pB2rBM; ` /Bmb Q7 Ry TBt2Hb-  
bBi2b HH i QM+2X

h?Qb2 jR9 p2+iQ`b KB;?i MmK2`B+ HHv bT M  
#mi bBM+2 i?2 i2KT2` im`2 T`Q}H2b Q7 M2 `  
B/2MiB+ H- i?2 ó2bb2MiB H /BK2MbBQMô Q  
i? M jR9X

q2 mb2 i?2 bBM;mH ` p Hm2b Q7 i?2 >:aöb p  
b2MbQ`b ó2bb2MiB H /BK2MbBQMôX

A7 >:a ? b ó2bb2MiB MHi/B2MB MabbBQMôH/ ;Bp2  
K2 bm`2K2Mi Q7 2[m H [m HBivX



















## Limitations

Due to both a lack of data and computation power, we mostly ignored the 3D case. Both shape packing and SVD methods can be adapted to 3D.

We do not know how exactly to construct a good significance function and we assume it has enough similar properties to “temperature” to make the SVD approach feasible.

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Any method to interpret the sensors based on historical data will slowly degrade in quality because of climate change.

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Any method to interpret the sensors based on historical data will slowly degrade in quality because of climate change.

For our SVD methods we ignored the fact that HGS can see some of the ocean even if it is on the land, this can be remedied but we didn't have the time to implement it.

## Conclusion

To solve the multi-objective optimization problem, we offer the circle packing approach and Dr. Nonomura's approach to optimally place the sensors.

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Tokyo

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Shape-Packing

SVD

More high-grade sensors

Data dependent

Japan

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SVD

Low-grade sensors

## Reference

r%b^bsPS@i rz-@%b^ rPbqGq\ Gbq<- sz bHMb<- YC@OG f%p- SHY3- sC@b^  
zPCrz zSzS- Y; P-q <CszSs bH ~\ ~Y^S 4-s; Y~@s a 4sCqfC@4%V- Q- ^@  
? beeYqp- @qi dP? zPGS>} ^SfCpS%bHys~W4 >|CEc .

[ -s P-q R -W VC^SPSOSps ...>y- W%W^ - ^- LS- ...>rP~\ eCSV- \ C%o\ ->  
- ^@OSP- WV~<G ,, - fCC^LzP sCC<S^ - ^@\ G s-q\ C^z CqpbqzPCbqCS- Y  
- ^- Yss b^ Lp~^@Q- sC@<bPCq^z @S Gq^zS Y- 4sbqzS^ Y@ q~sSL cil {Q\ \  
...: fCC^LzP Hqss ~Y- ^Cb~s fCqS- Yedp" YL bH.: zCqf- ebq@C^sY%oo^@..S@  
seCC@- e-4YSPQs ^bzG , eeY a ezi>I\_fdg= |vwu |vwu[ -q|CECE



[ -s P-q R -W OS- \ SPSy- ^- W> VC^SPSOSips- ...>y- W%odW^ - ^- LS- ...>- ^@  
 rP~\ eCSV- \ C%od -i? C\ b^szq zB^ bHZPC cil {Q\ <bPGq^z @SYHqS ~Y^ ^Cb-s  
 eq" YL bH.: zCqf-ebq@C^sS%oo^@..S@seCC@ a ezi BteqCs> |DfcDg  
 |uCEID |uCEv>, ~L |CECE

Ki,, i dCz%o GSpz; b-qCS' , z\ bsePGq yPG\ b@%o \ Ssi r~^@bL d~4i> |CEE  
 VCY%o b^zS^z Y- ^@Y< Y..S@si

VCLb ^- \ - @>V~\ S] - WS-y- W%odW] - L-z>VCS~W, s-S^ -s-br-s W^ ~IS  
 r- Sb>y- W ] b^b\ ~q - ^@?- S-Wys-4 W'bi ? Ccq\ S- ^zq\ sC@Hsz LqCC@%o  
 sC^sbqsCC<zB^ - YbqP\ i