King Abdullah University of Science and Technology KAUST

An adaptive Ensemble Optimal Interpolation for cost-effective assimilation in the Red Sea

Habib Toye[1], Peng Zhan[1], Furrukh Sana[1,2], and Ibrahim Hoteit[1]

[1]King Abdullah University of Science and Technology, Thuwal, Saudi Arabia,

[2]Harvard Medical School, Massachusetts General Hospital, USA

Arctic Ocean
Barents Sea
Iceland
Sweden
Russia
Ireland
Denmark
Poland
Ukraine
Kazakhstan
Mongolia
France
Austria
Romania
Sea of Japan
North Atlantic Ocean
Spain
Italy
Kyrgyzstan
South Korea
Greece
Turkey
Turkmenistan
East China Sea
Morocco
Tunisia
Syria
Iraq
Iran
Afghanistan
Pakistan
Western Sahara
Algeria
Libya
Egypt
Nepal
Philippine Sea
Saudi Arabia
India
Myanmar (Burma)
Oman
Mali
Niger
Thailand
Vietnam
Chad
Sudan
Yemen
Bay of Bengal
Gulf of Thailand
Burkina Faso
Guinea
Gulf of Aden
Arabian Sea
Nigeria
Ghana
Ethiopia
Malaysia
South Sudan
Laccadive Sea
Gulf of Guinea
Somalia
Indonesia
Gabon
Kenya
DRC
Tanzania
Angola
Zambia
Mozambique
Namibia
Zimbabwe
Indian Ocean
Botswana
Madagascar
South Atlantic Ocean
South Africa

France
Austria
Ukraine
Kazakhstan
Romania
Italy
Uzbekistan
Greece
Turkey
Turkmenistan
Tunisia
Mediterranean Sea
Syria
Iraq
Iran
Libya
Egypt
Saudi Arabia
Oman
Chad
Sudan
Yemen
Gulf of Aden
Ethiopia


France
Austria
Ukraine
Kazakhstan
Romania
Italy
Uzbekistan
Greece
Turkey
Turkmenistan
Tunisia
Mediterranean Sea
Syria
Iraq
Iran
Libya
Egypt
Saudi Arabia
Oman
Chad
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Yemen
Gulf of Aden


France
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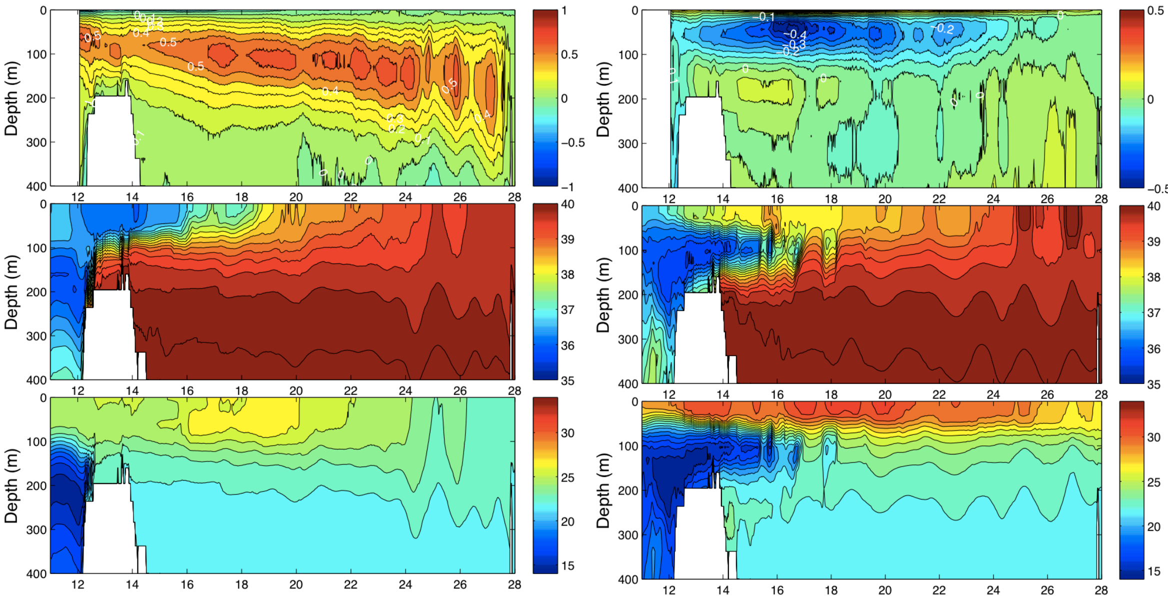
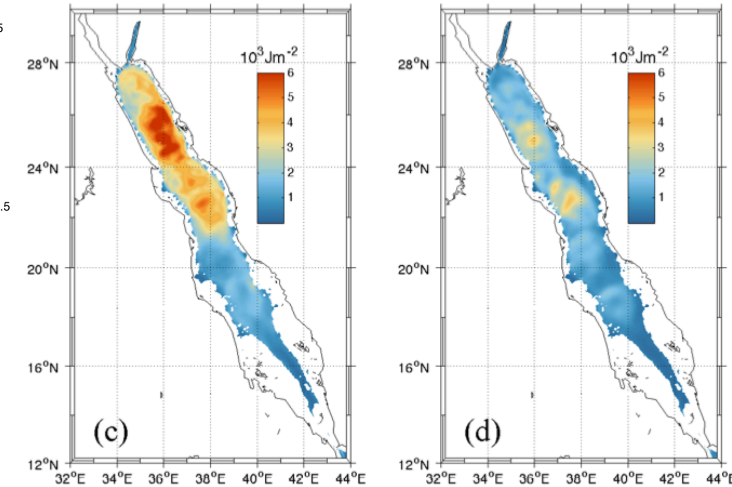
Turkmenistan
Turkey
Tunisia
Mediterranean Sea
Syria
Iraq
Iran
Libya
Egypt
Saudi Arabia
Oman
Niger
Chad
Sudan
Yemen
Gulf of Aden
Ethiopia
2,000.00 km
0

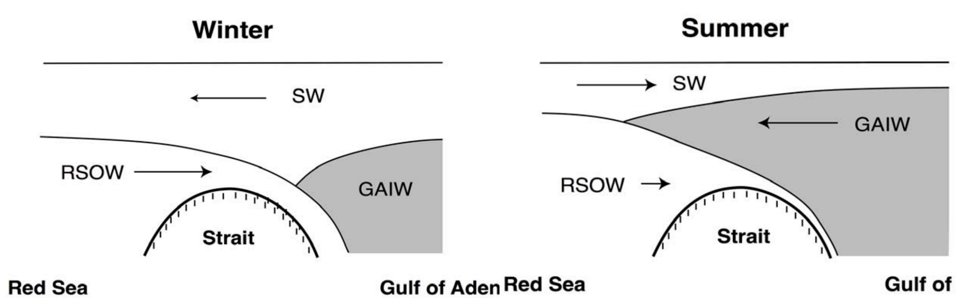
Seasonal Variability on the Dynamics



Yao et al. (2013 a, b)



Zhan et al. (2016)



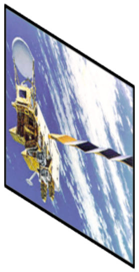
Smeed et al. (2004)

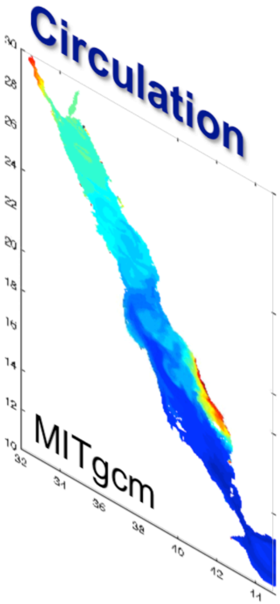
- **A stationary ensemble-covariance may not be appropriate for the Red Sea**

➔ to sample stationary-variant covariances adapted for each “season”

Data assimilation

Data assimilation

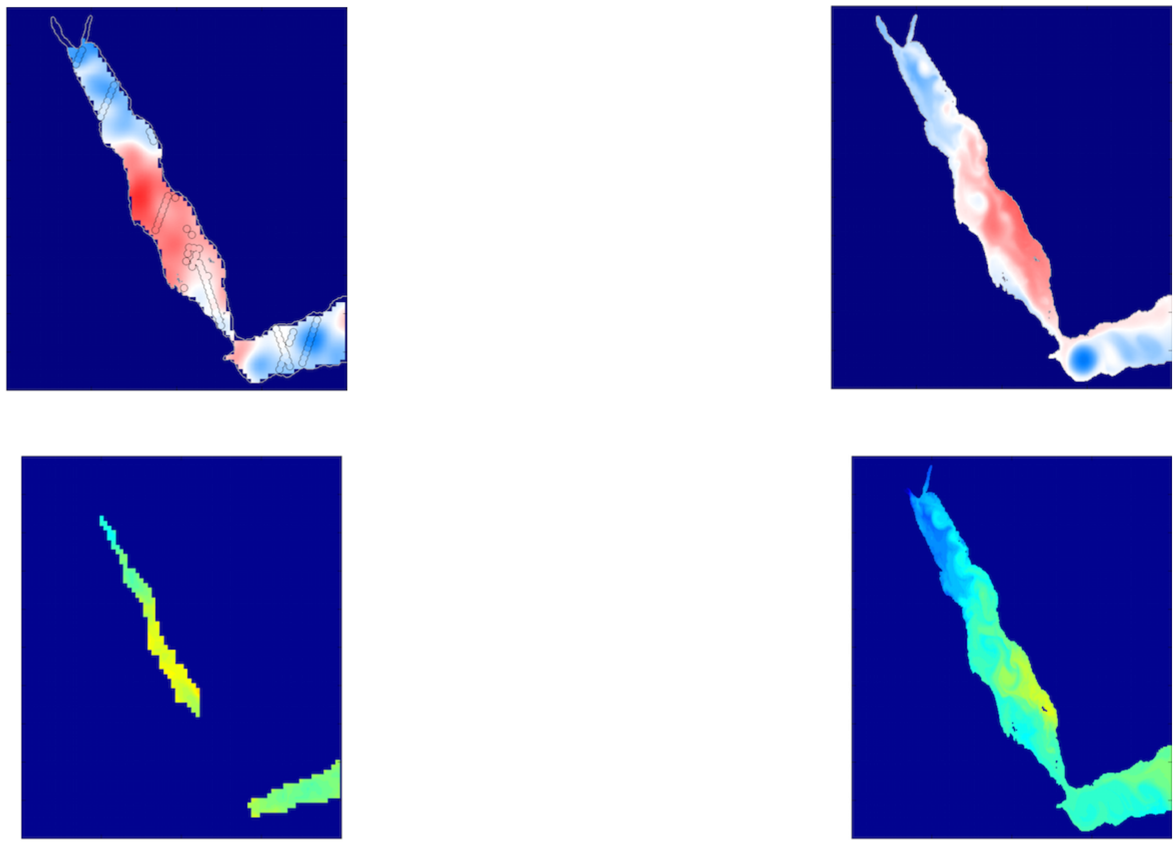




data

model

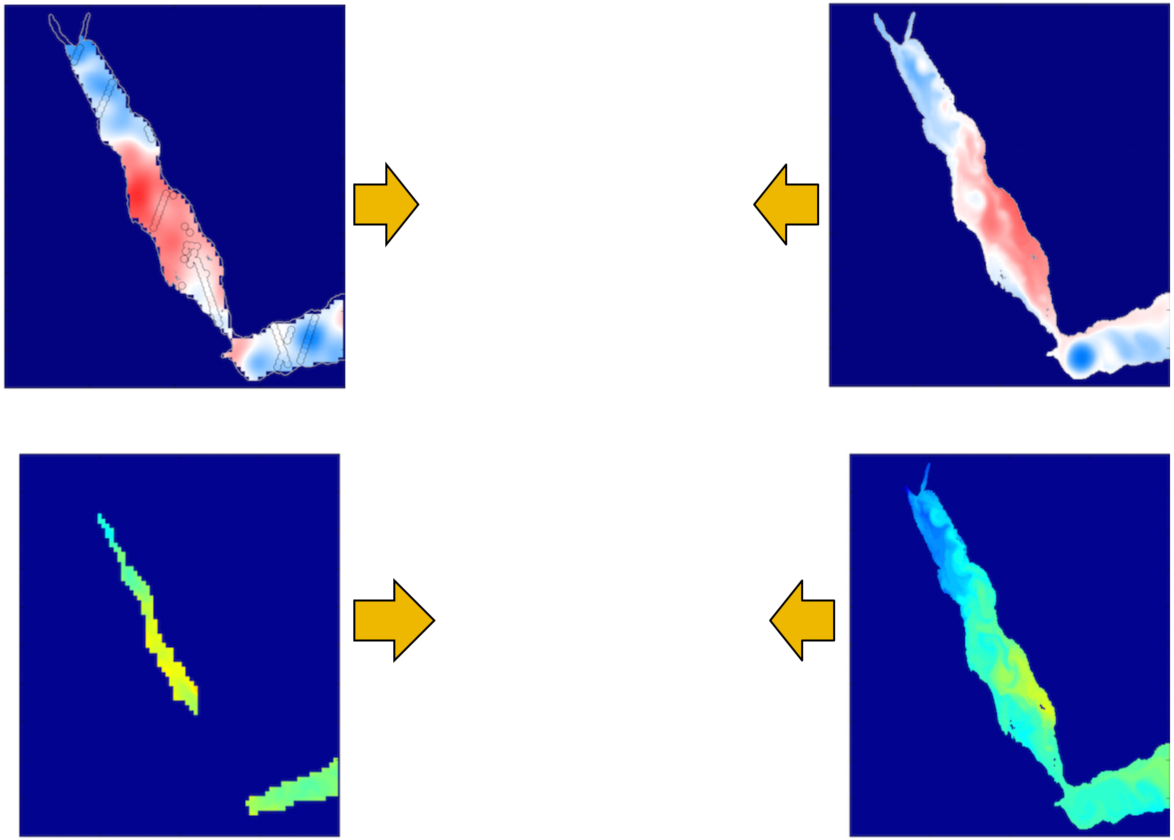
Data assimilation



data

model

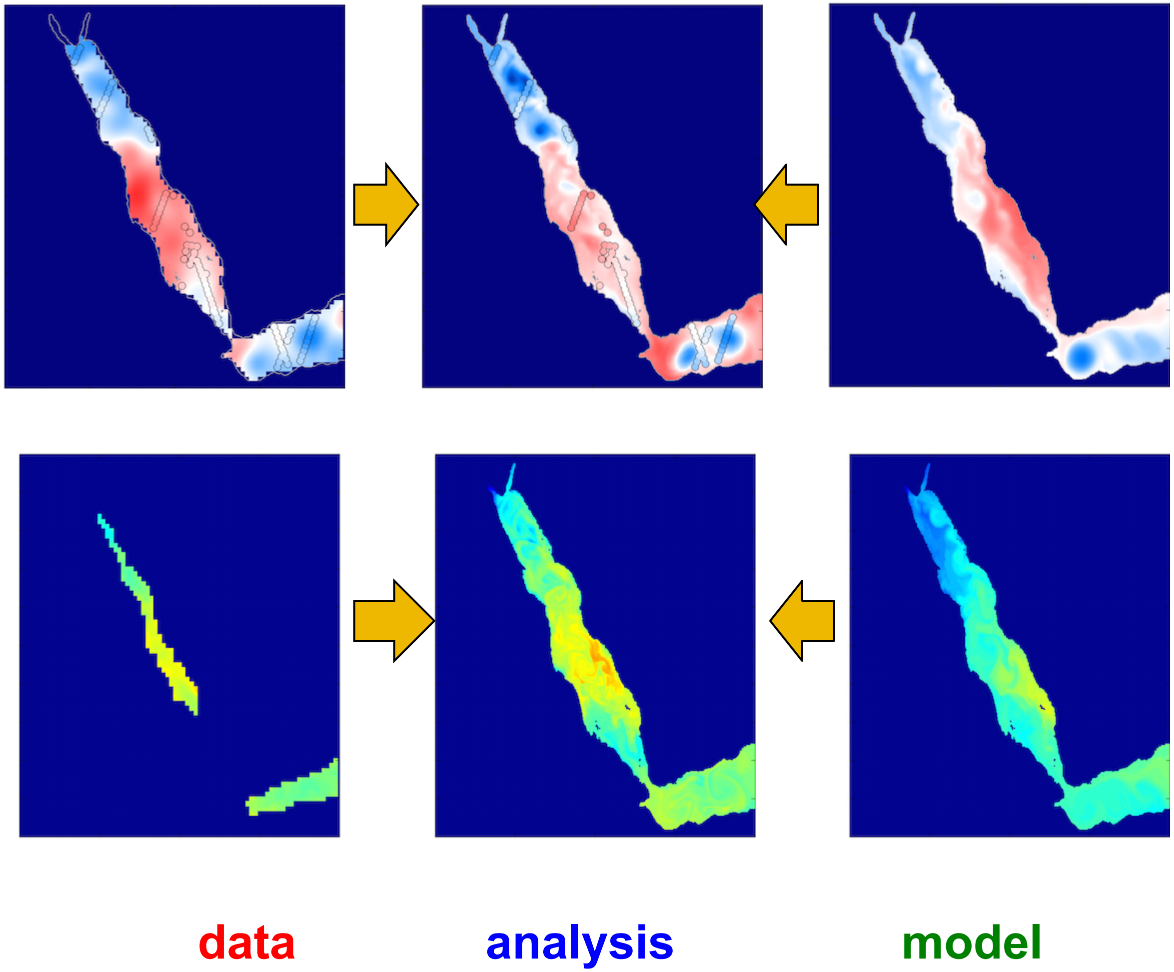
Data assimilation



data

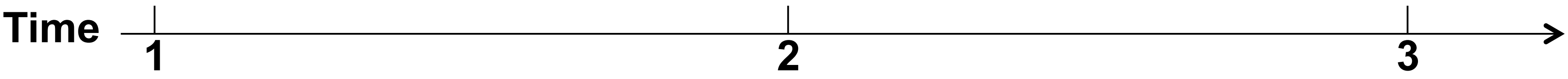
model

Data assimilation



Data assimilation

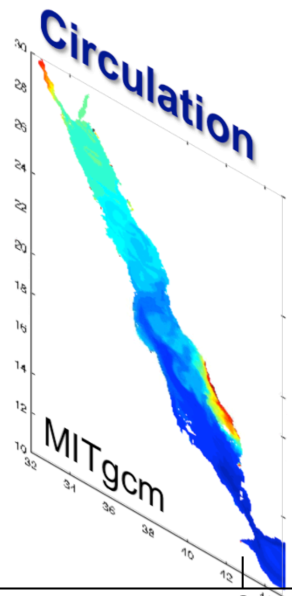
Data assimilation



Data assimilation

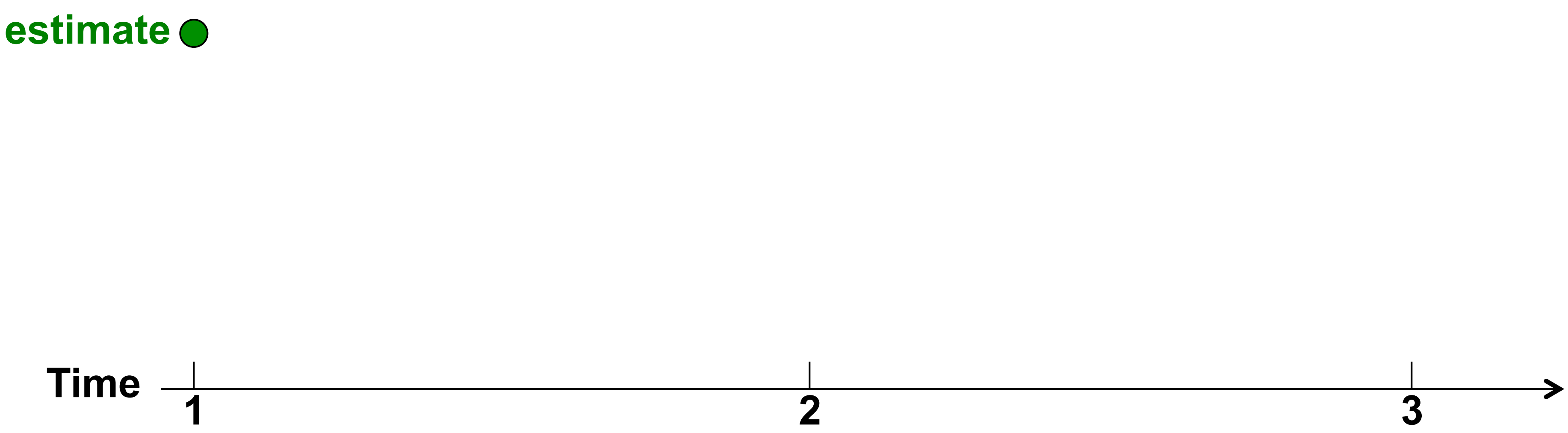
estimate

x^b



Time 1 2 3

Data assimilation



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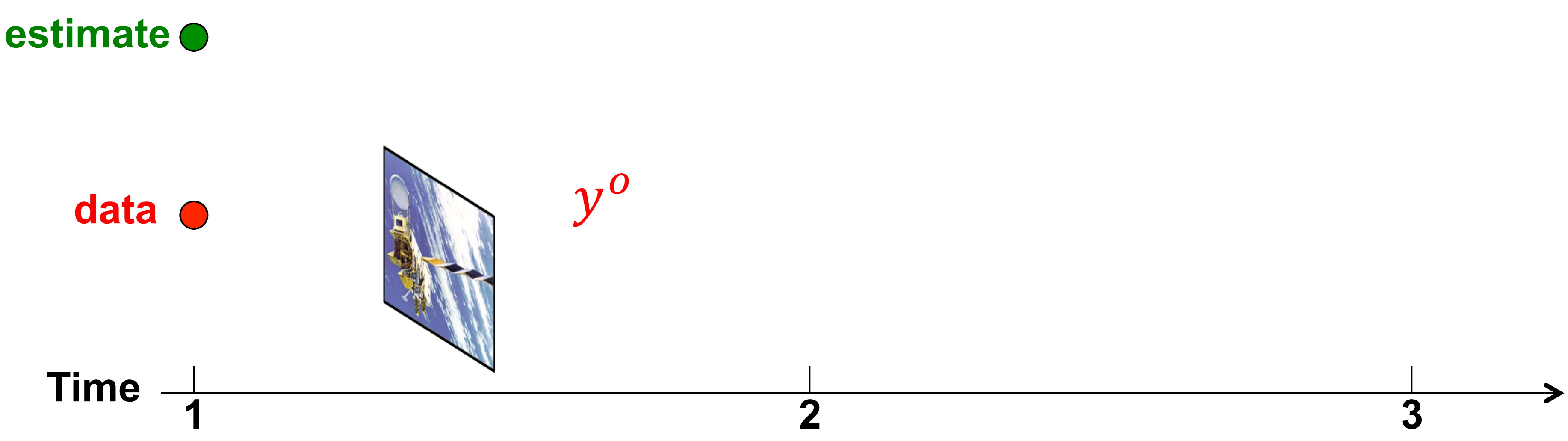

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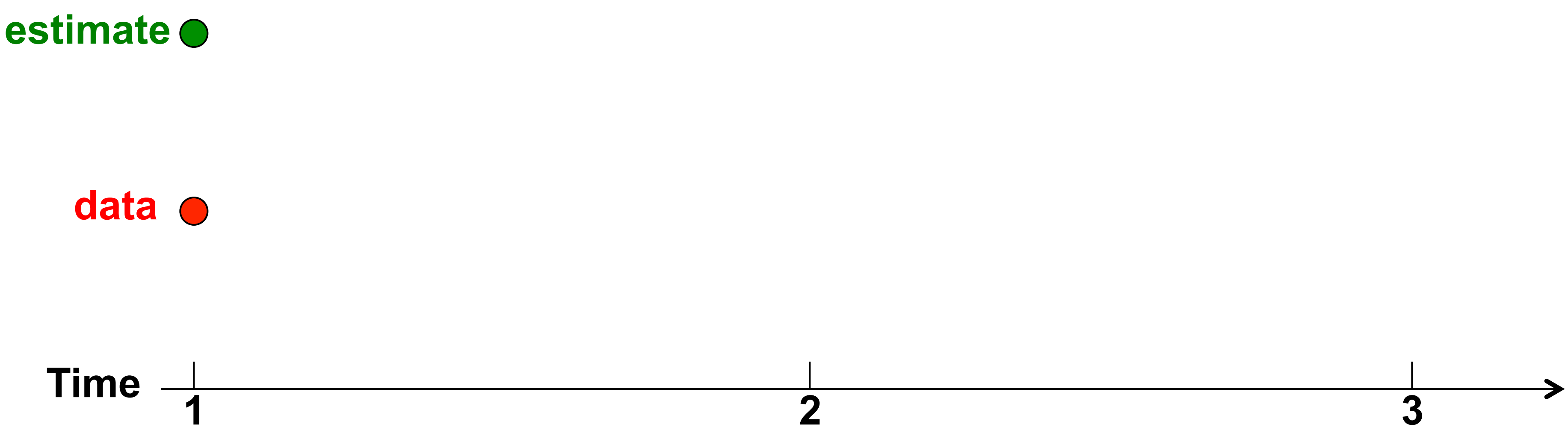

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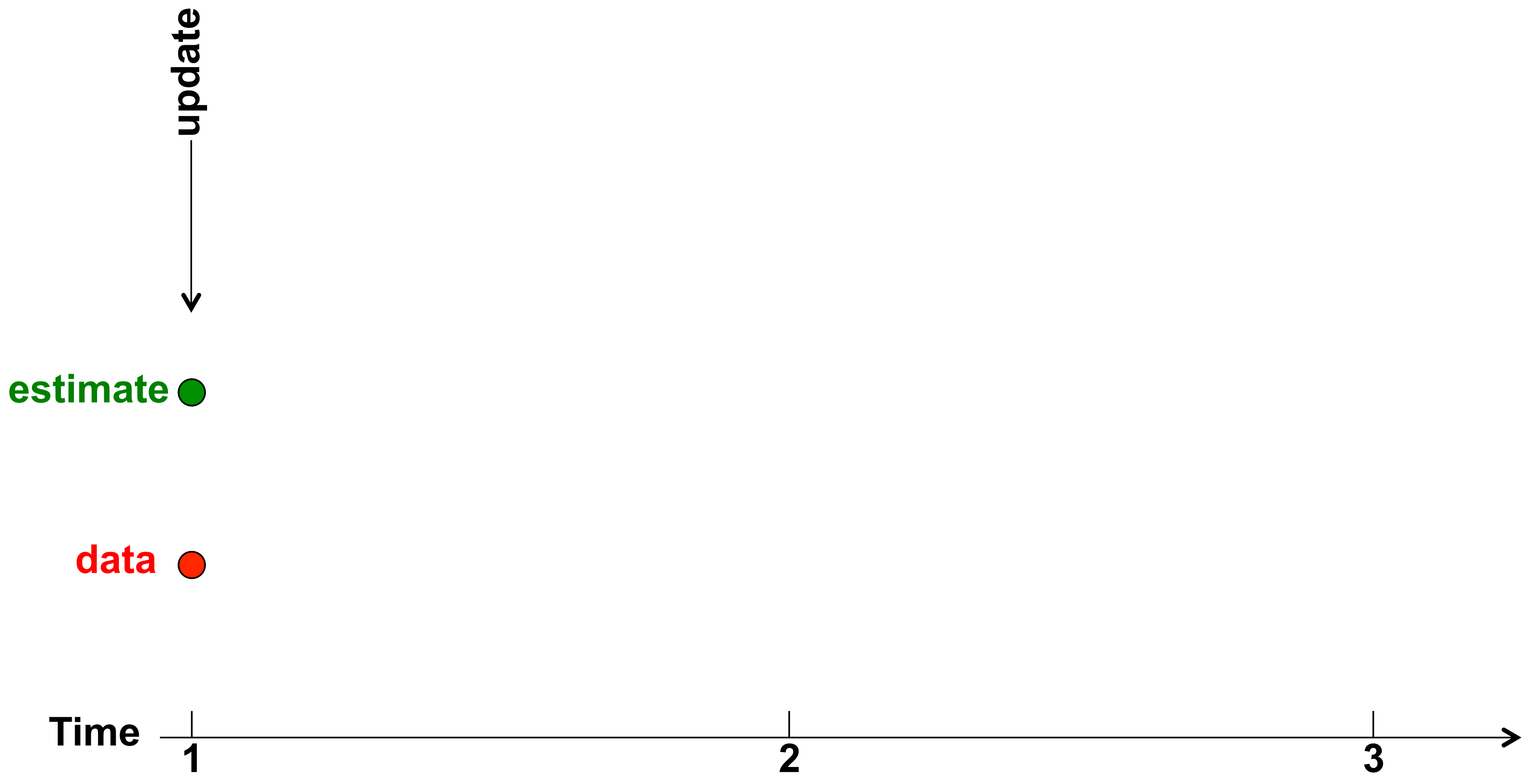

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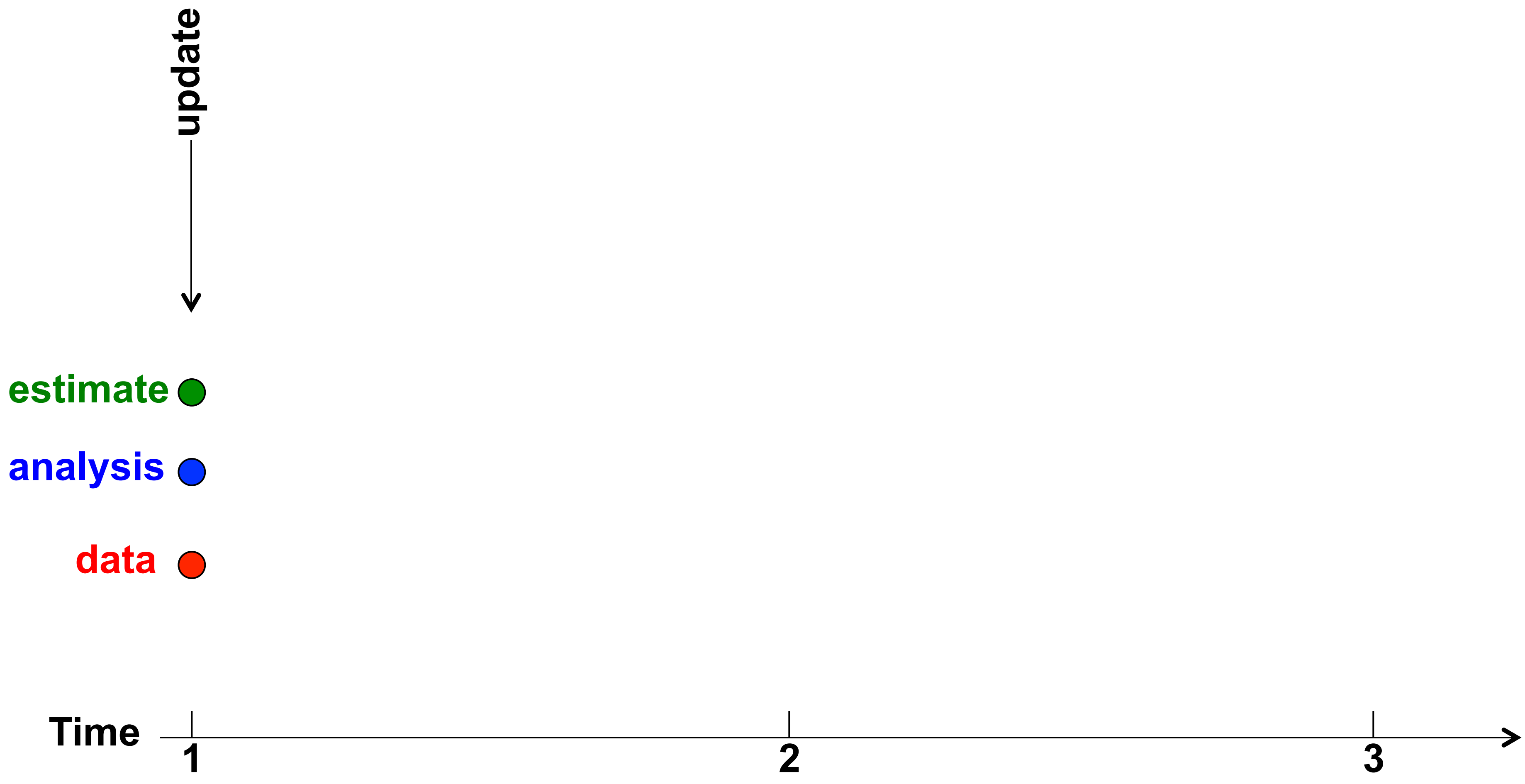

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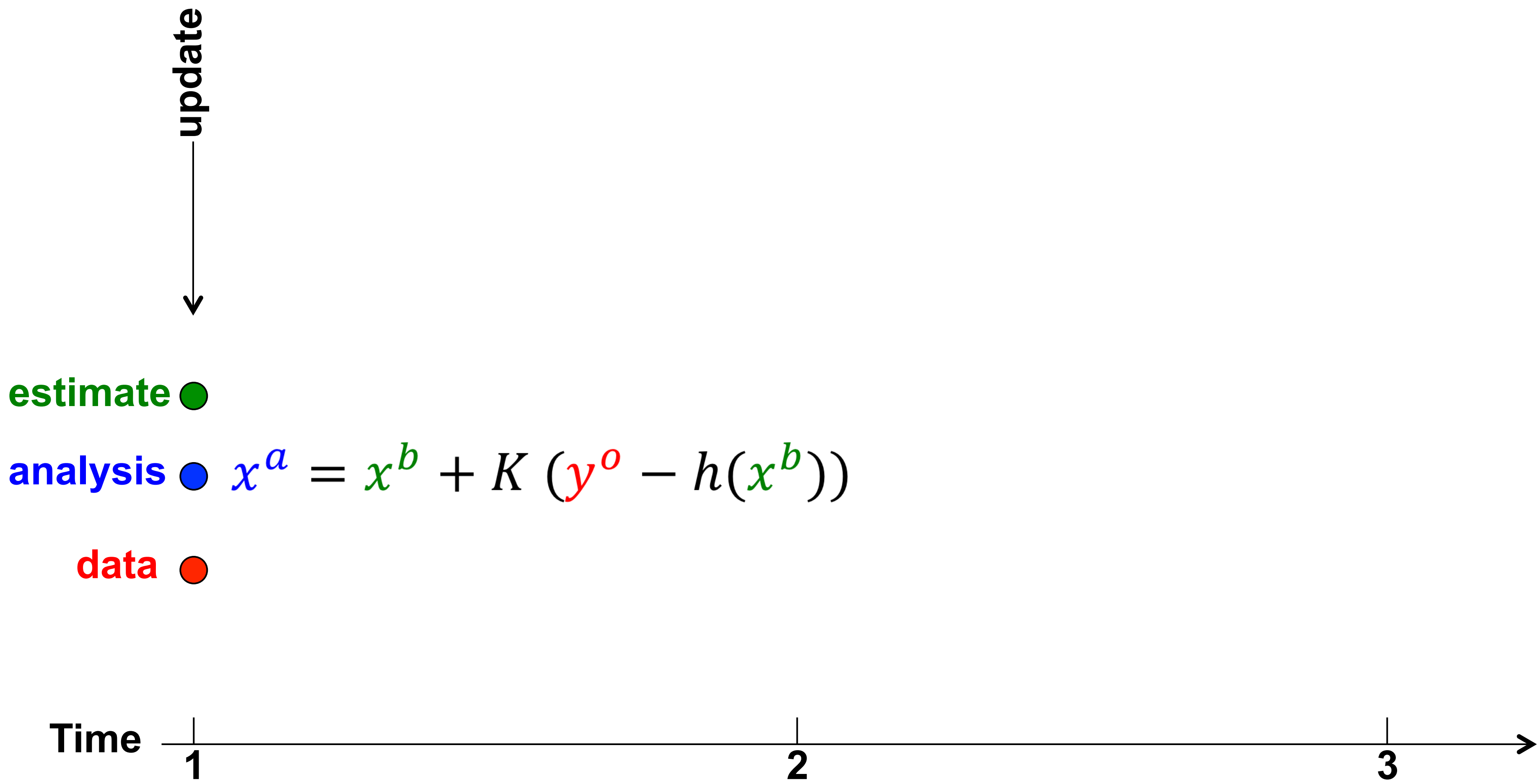
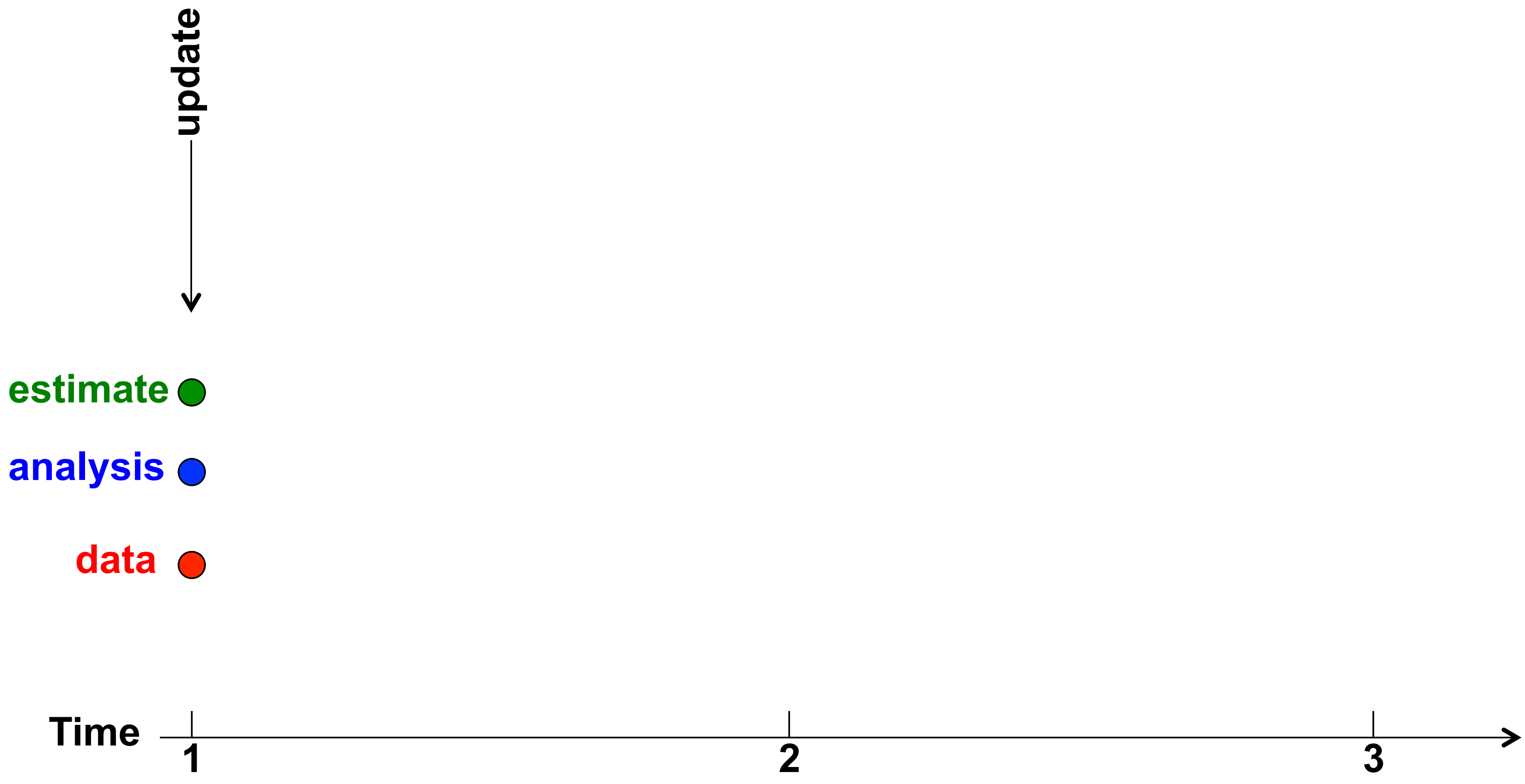
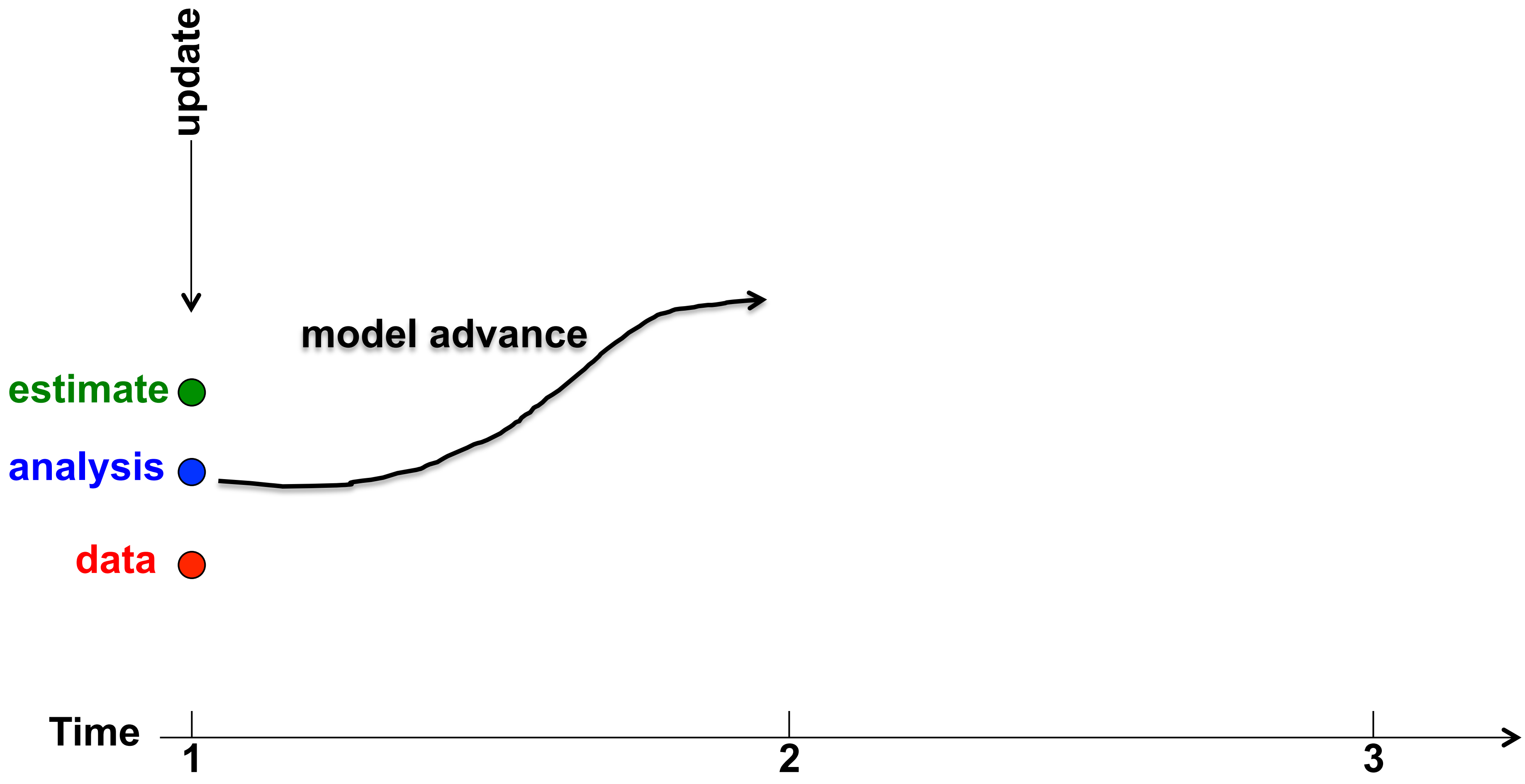


$$x^a = x^b + K\left(y^o - h(x^b)\right)$$

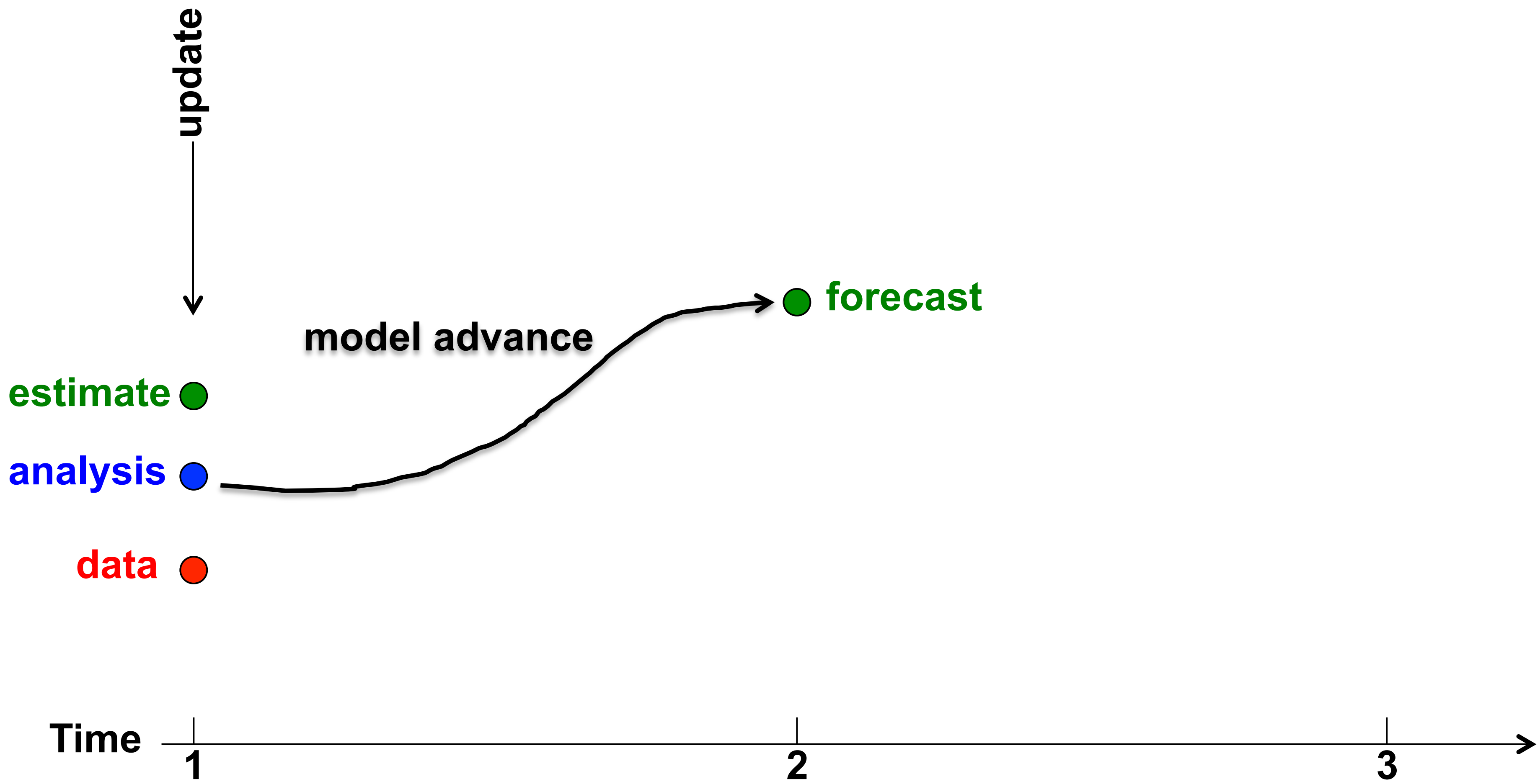
Data assimilation



Data assimilation



Data assimilation



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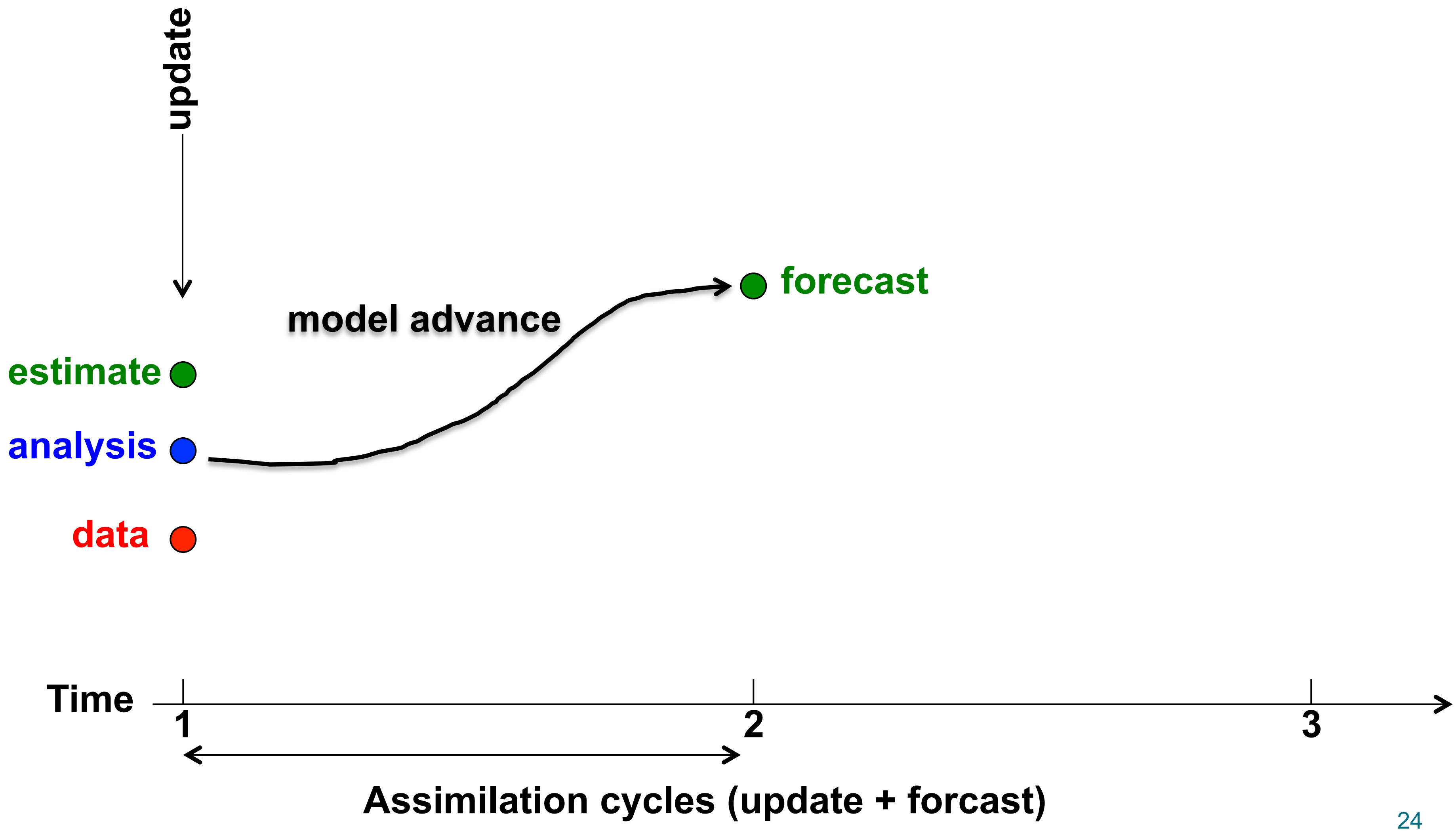

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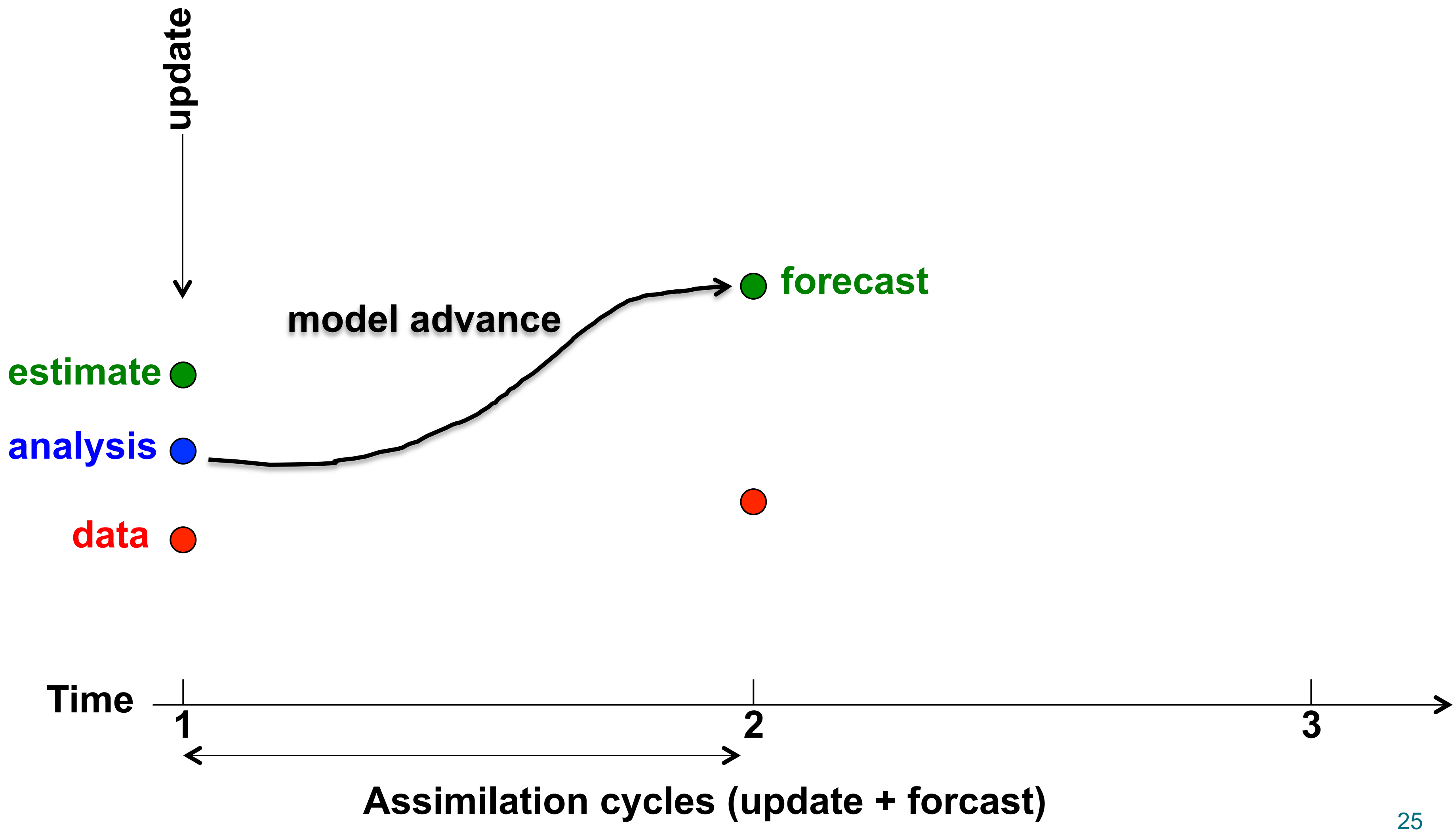

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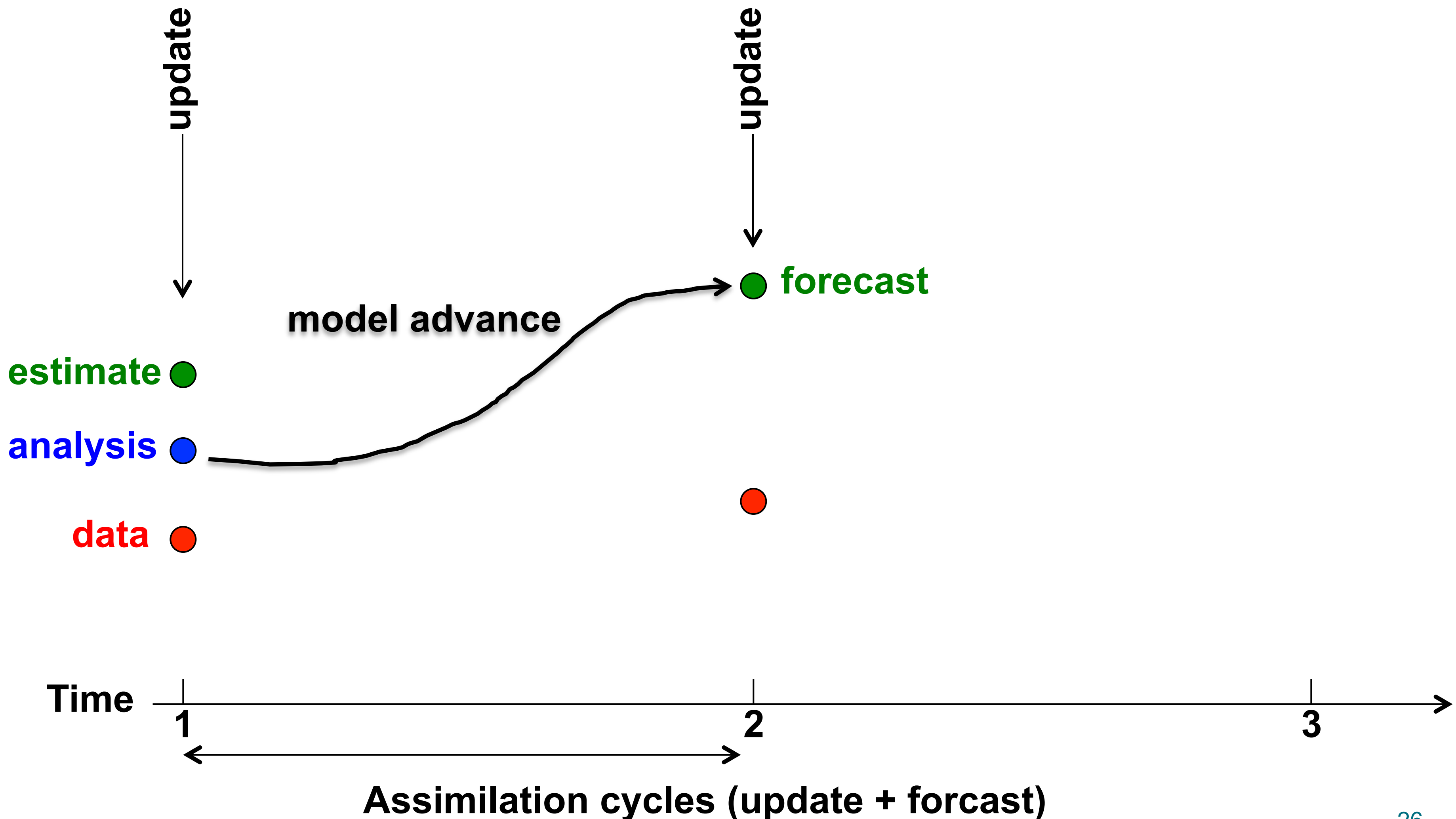

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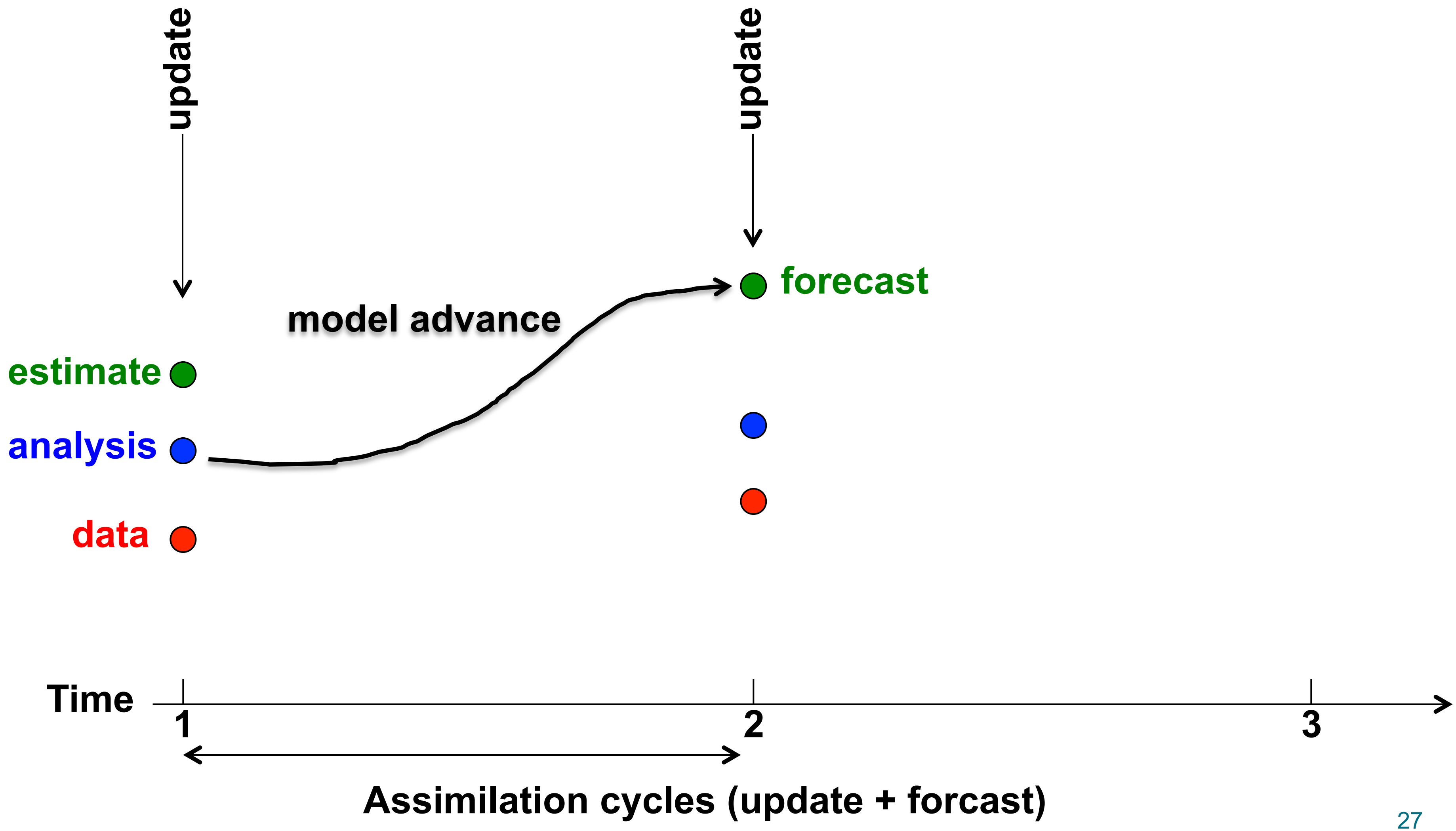

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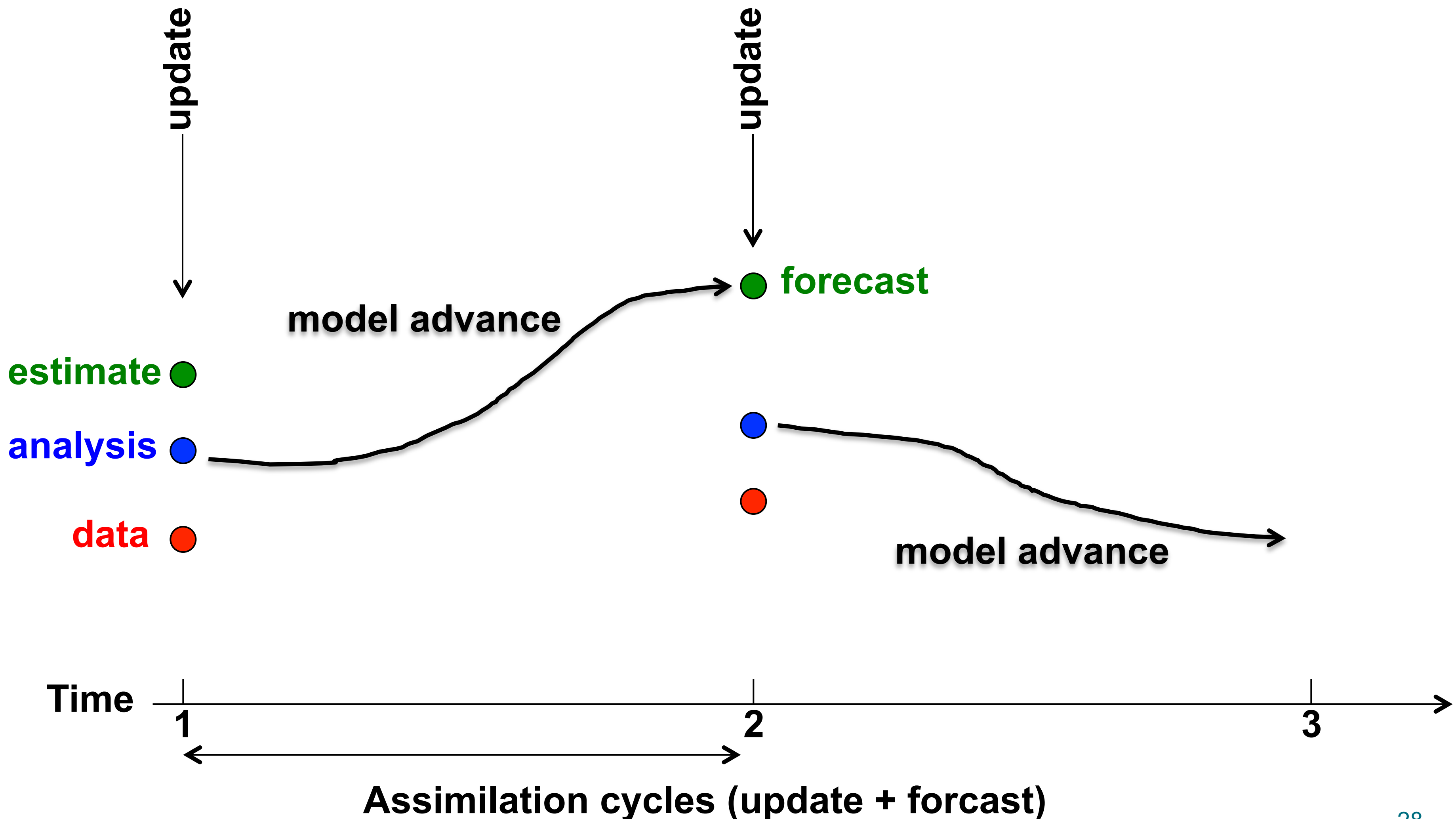

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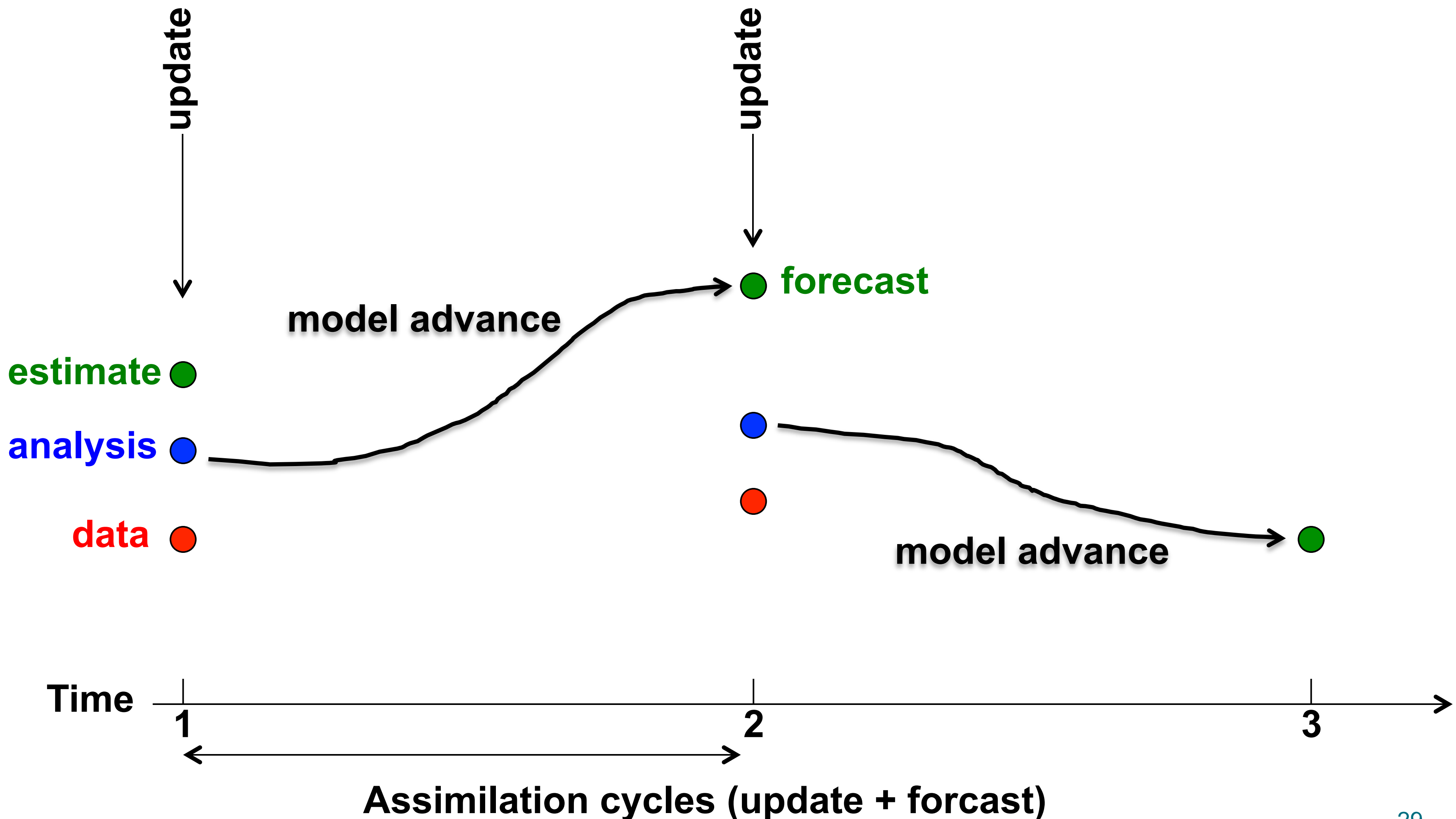

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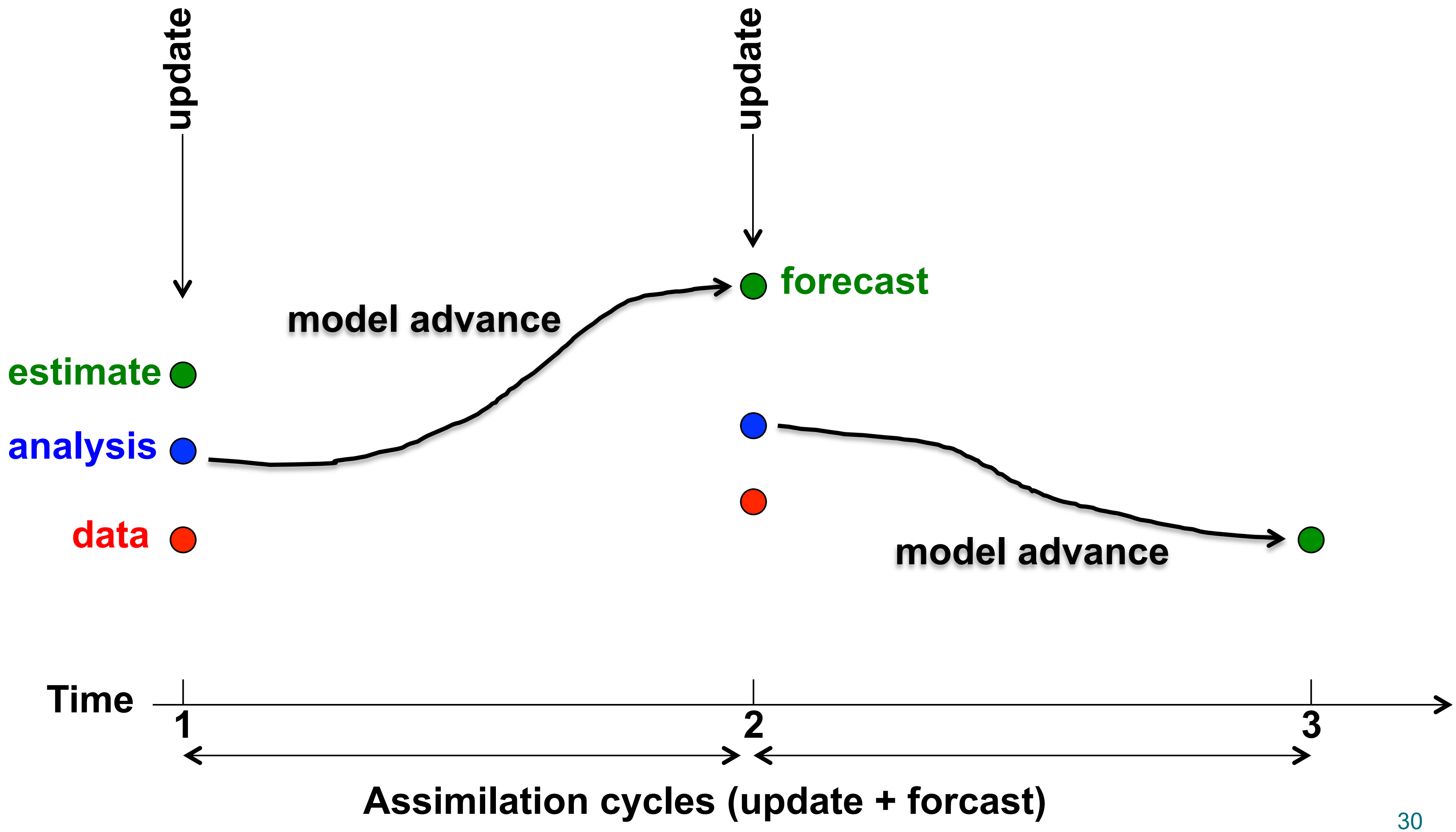

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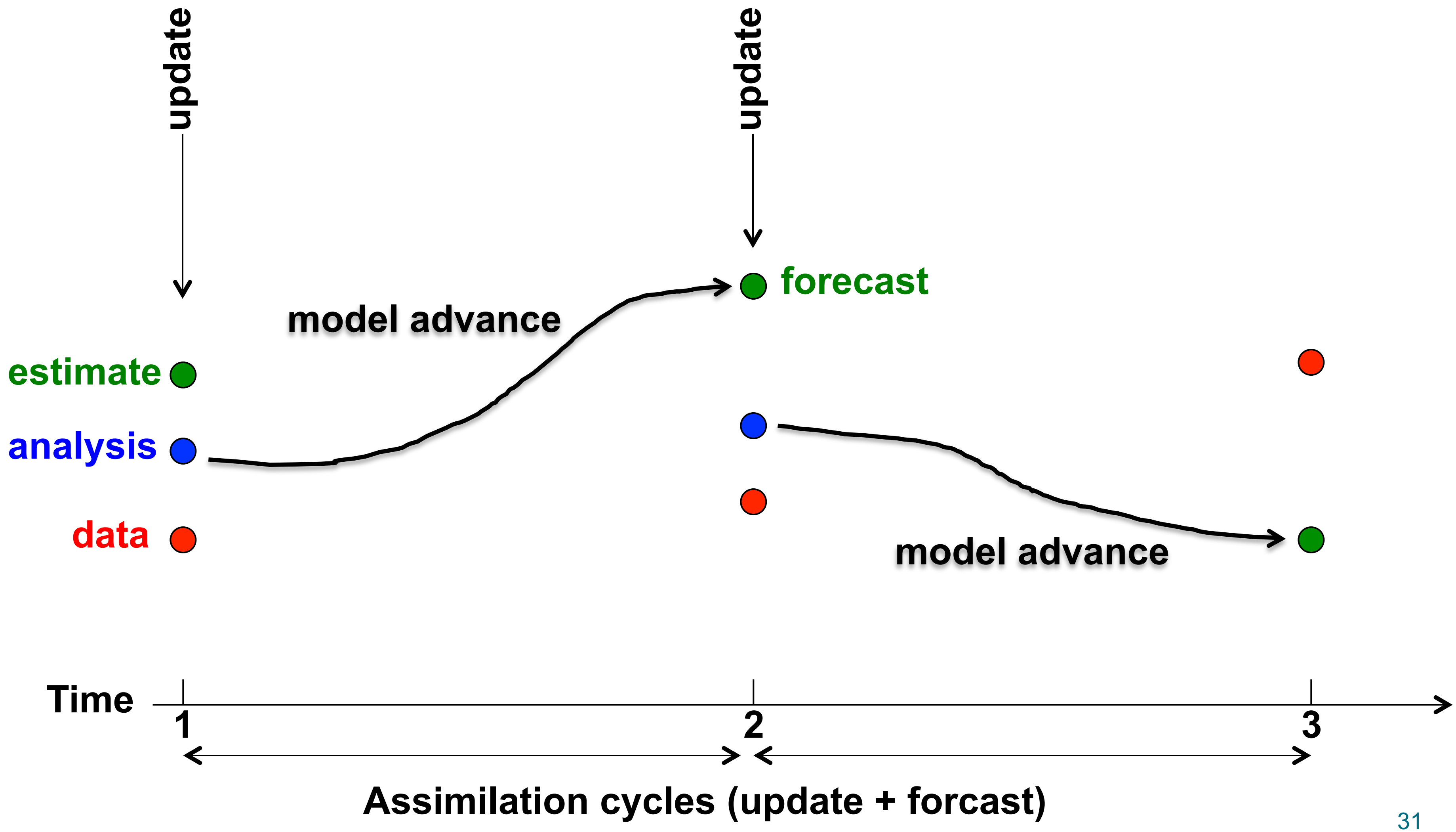

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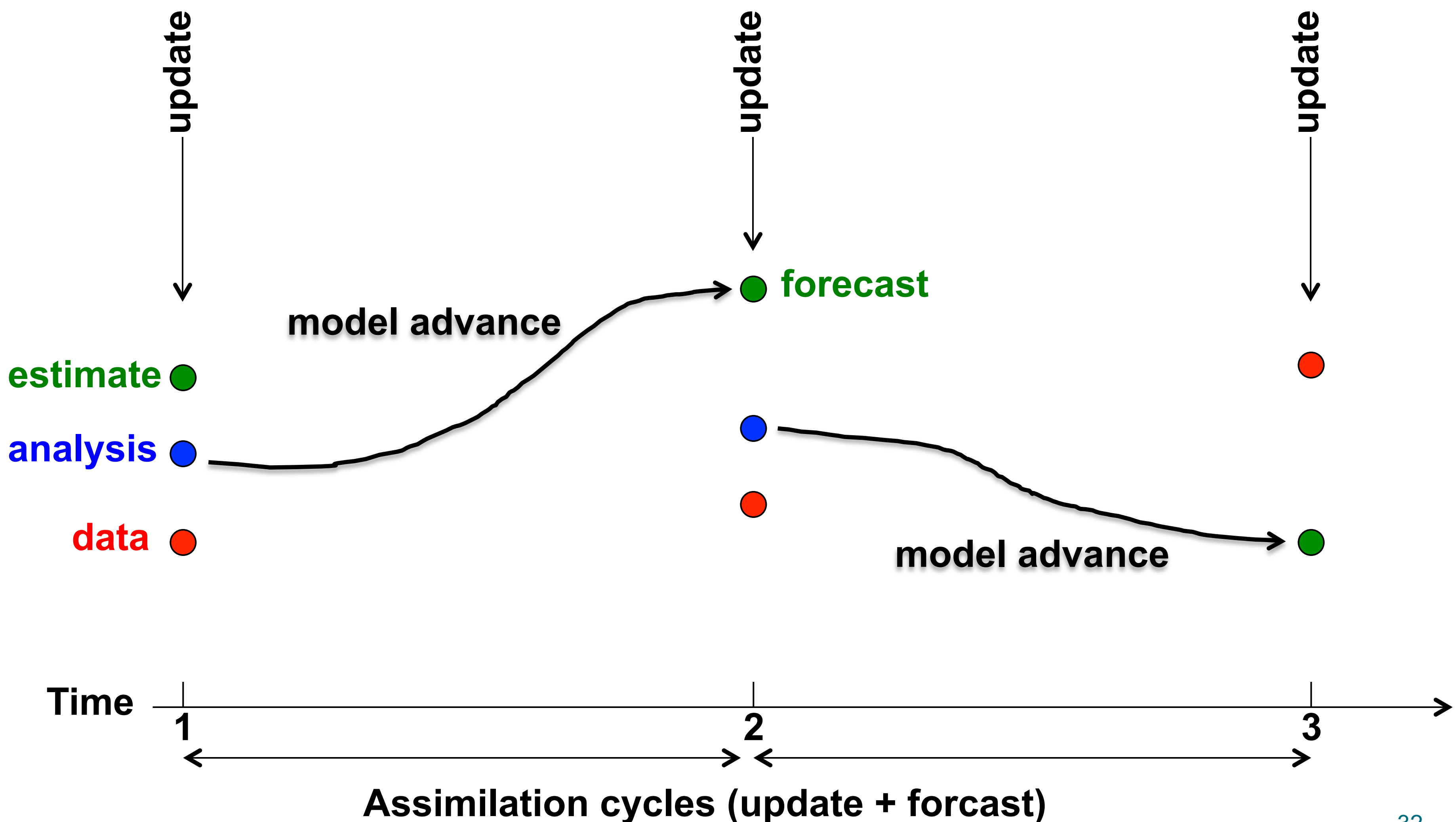

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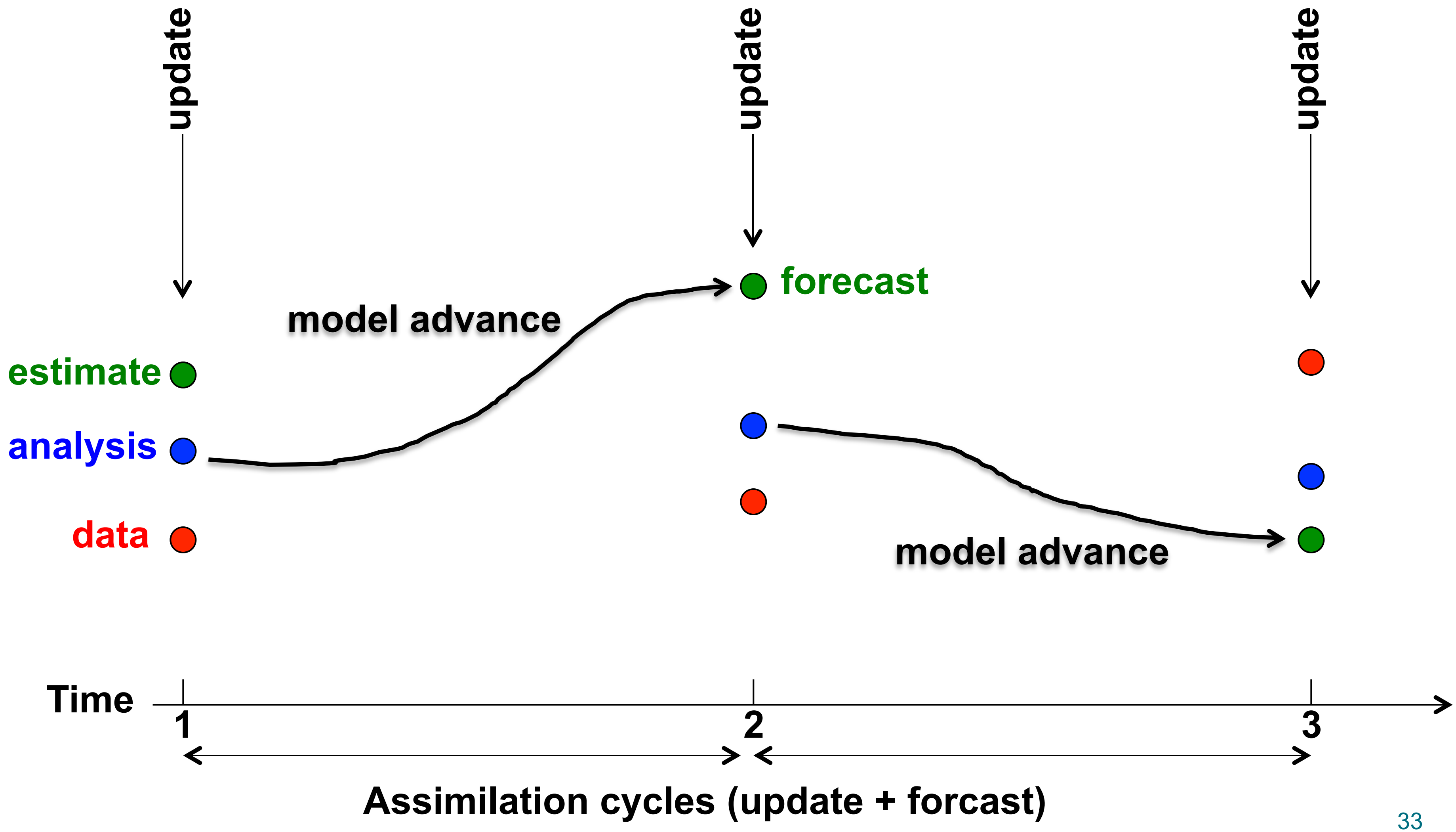

Ensemble data assimilation

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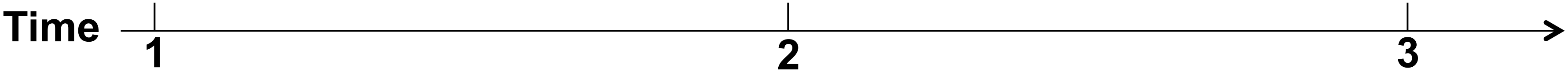

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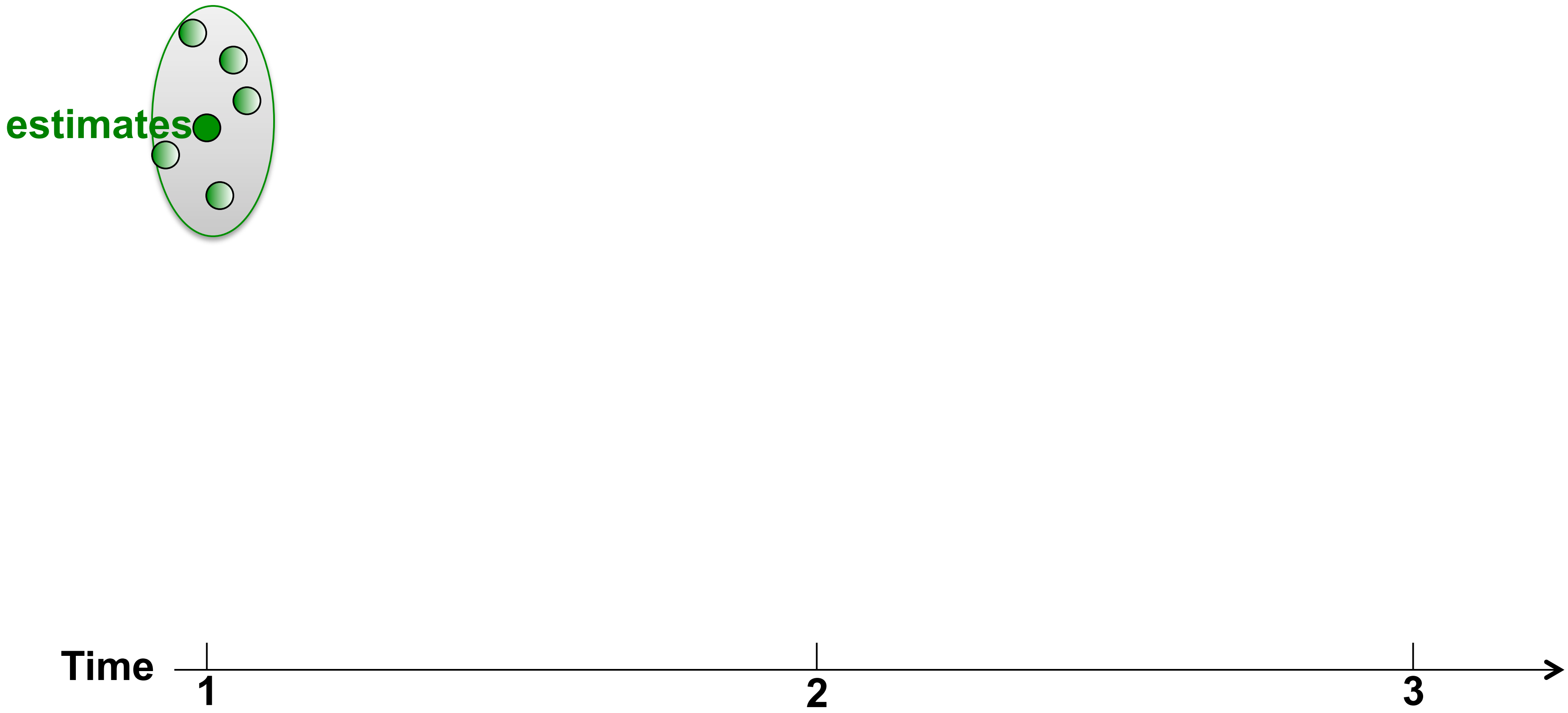

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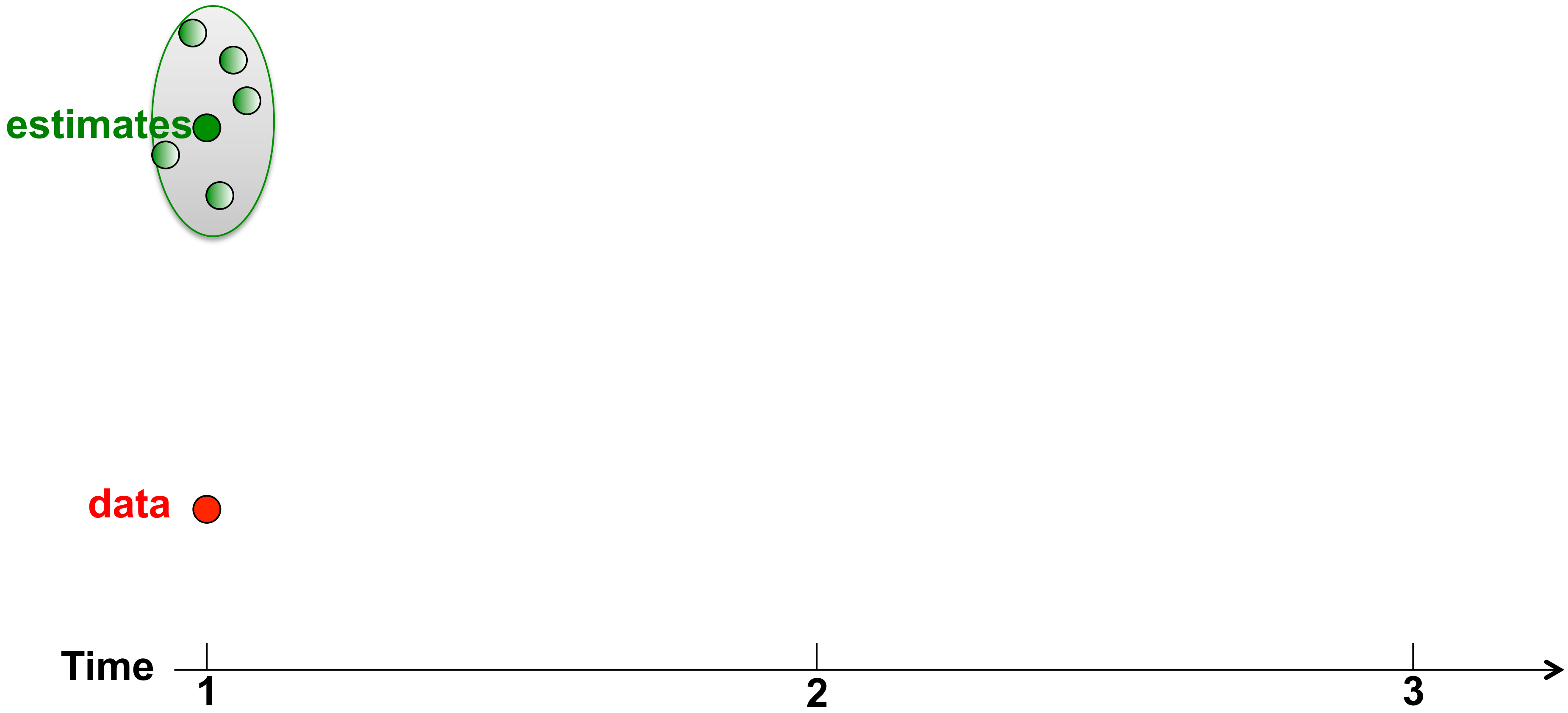

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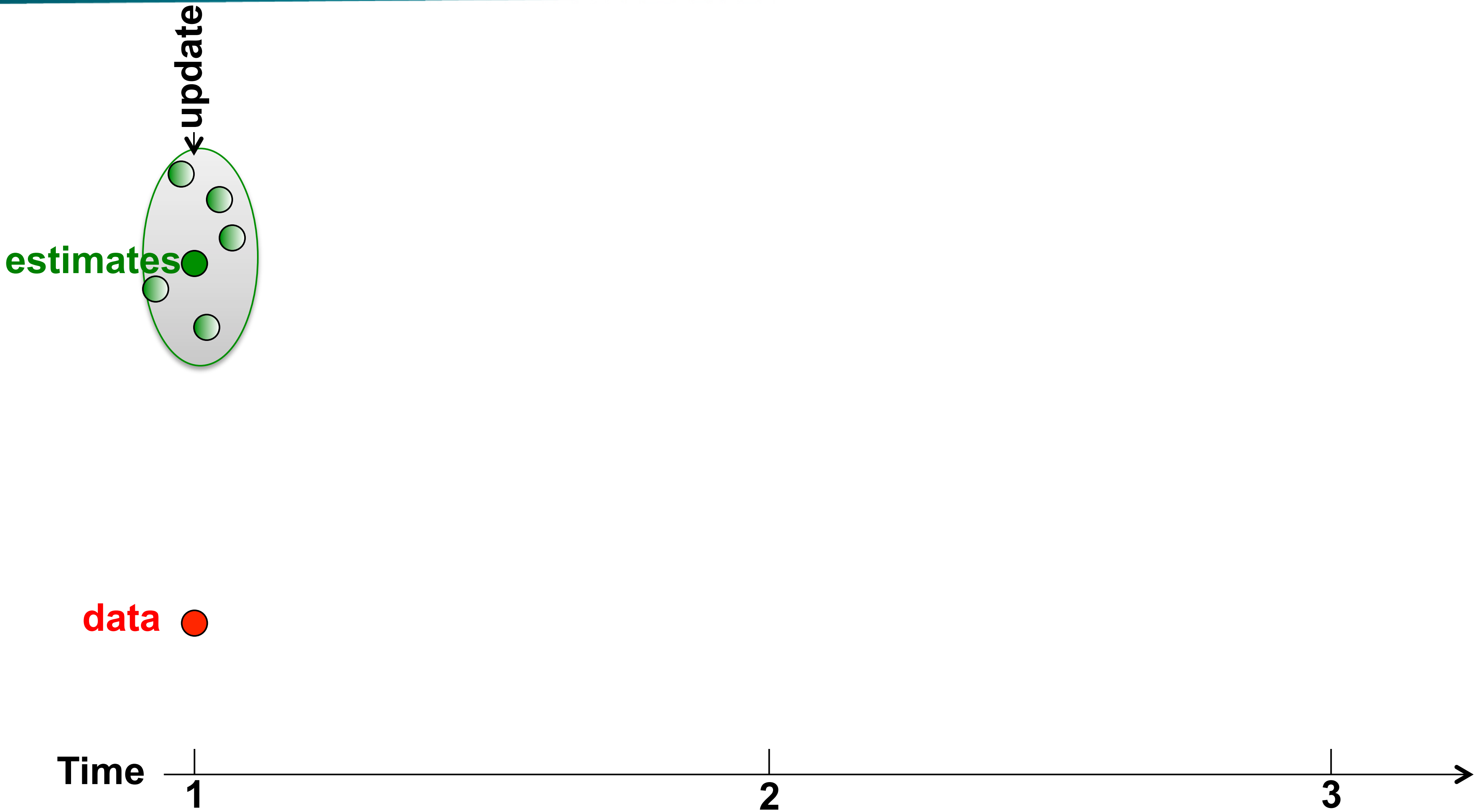

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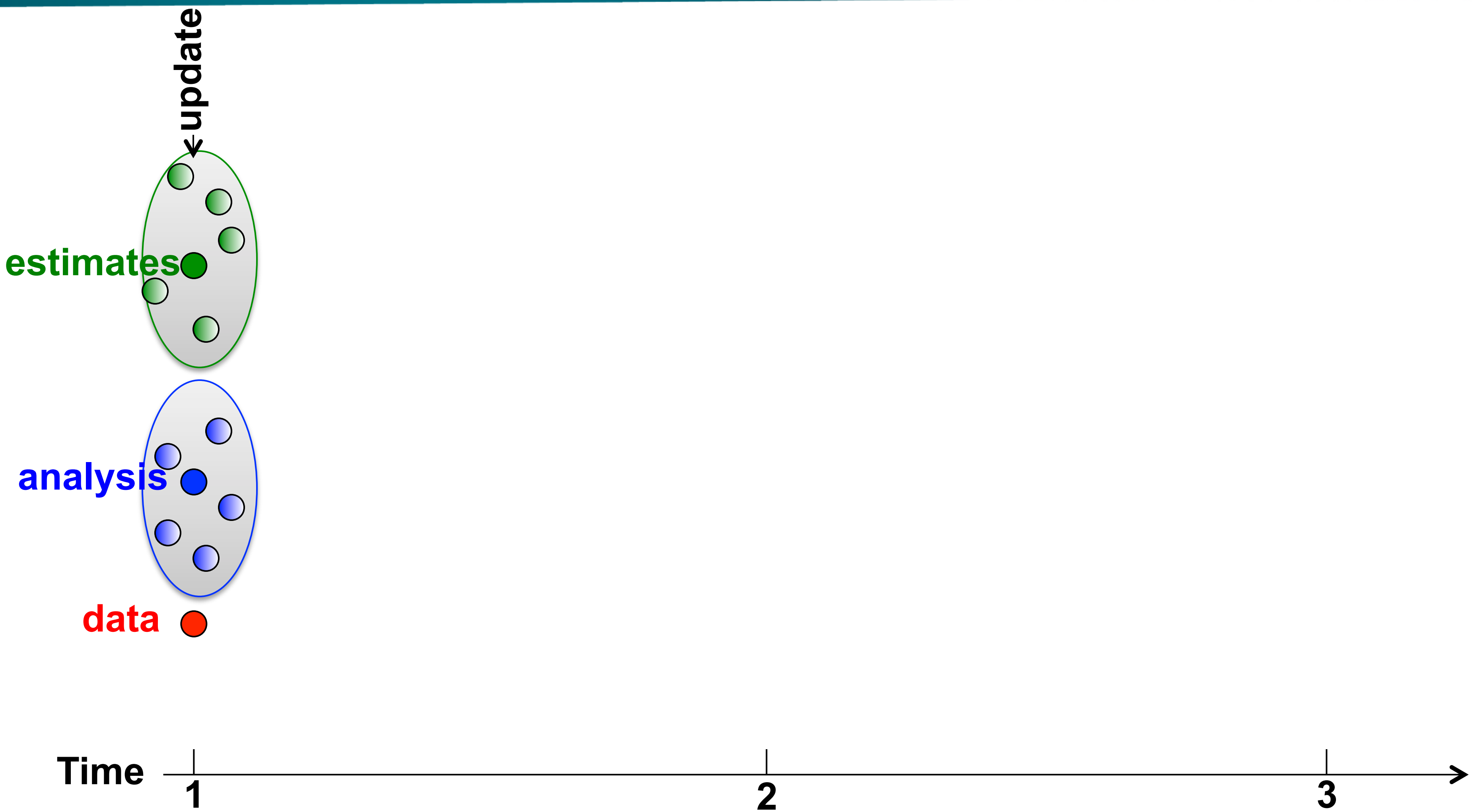

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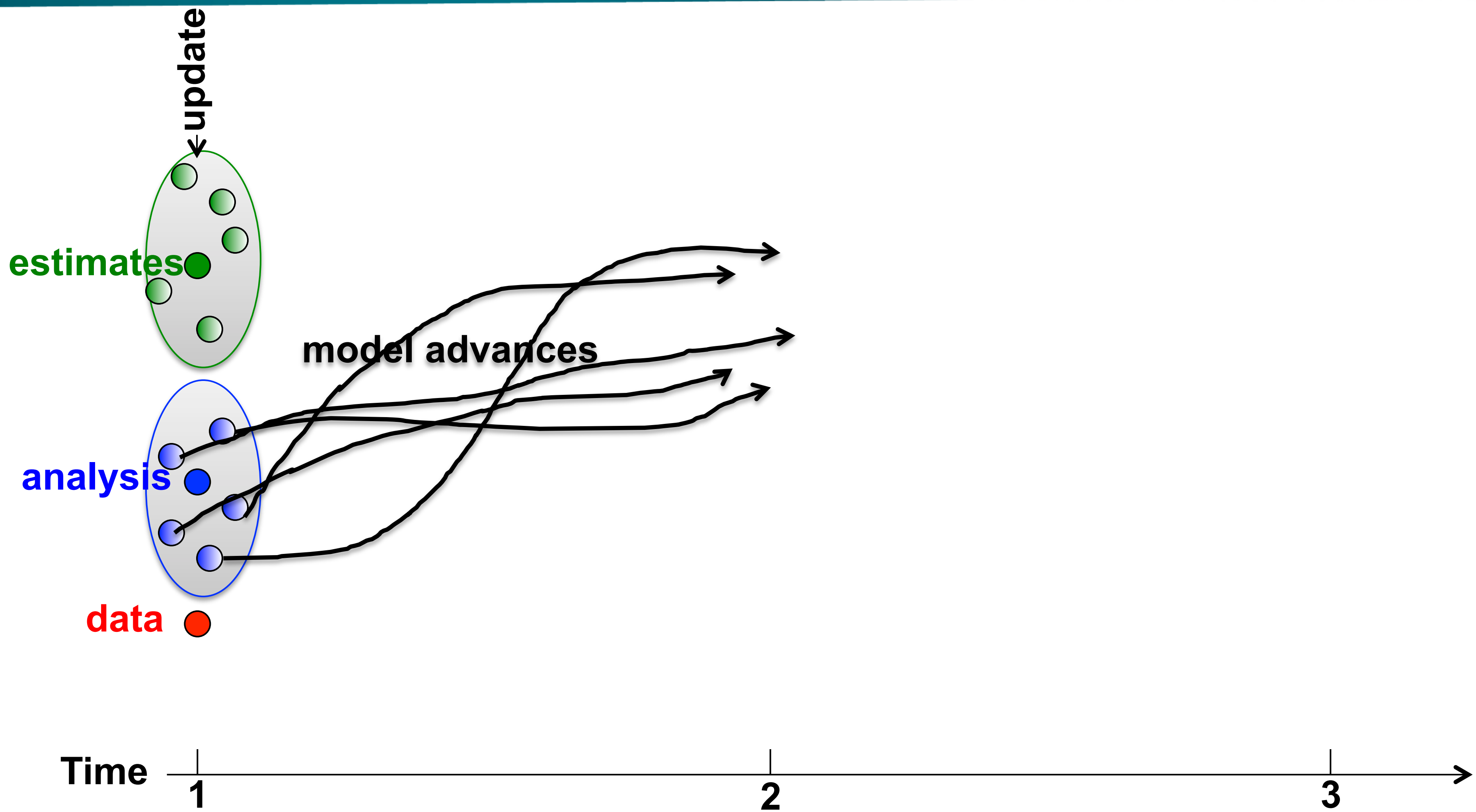

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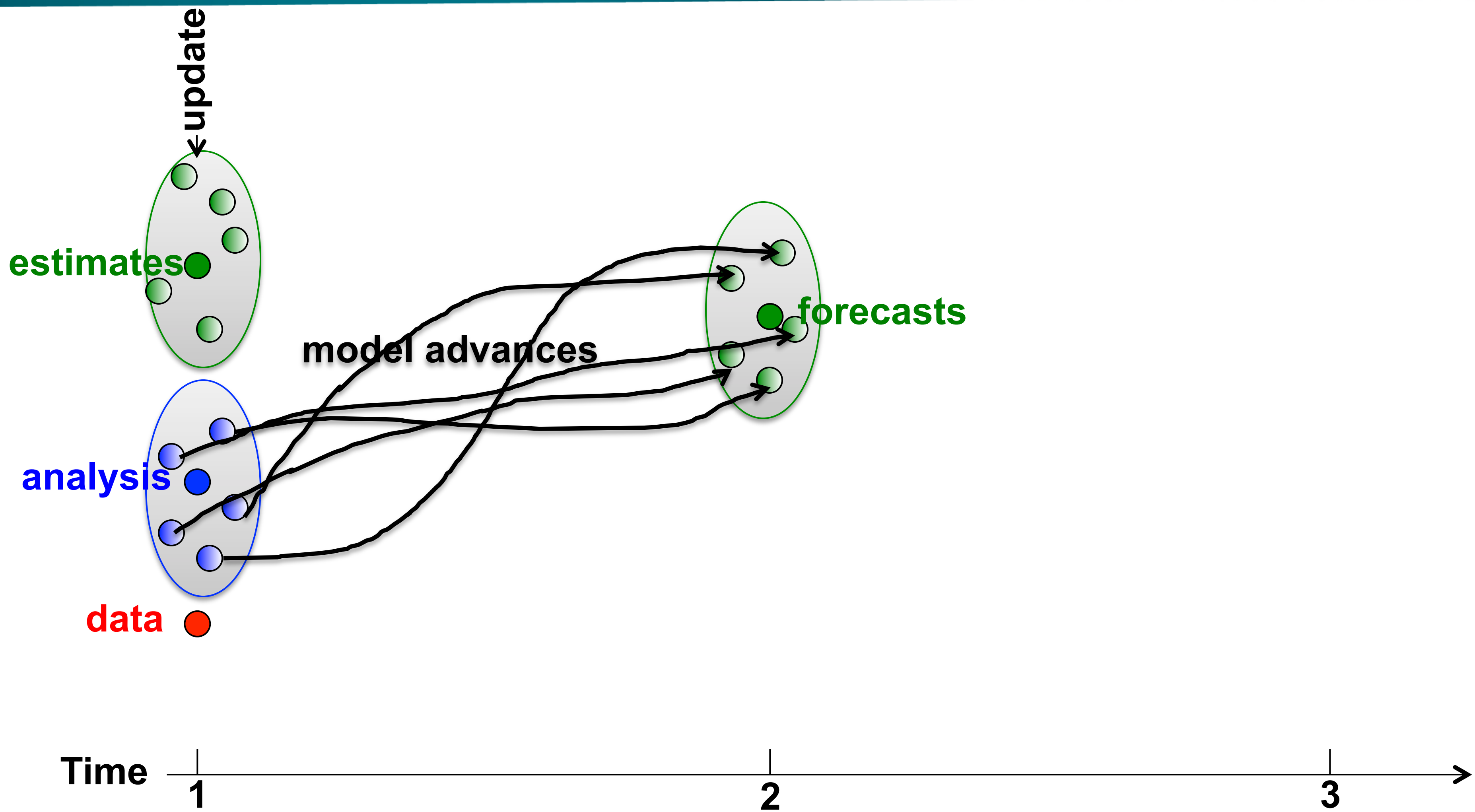

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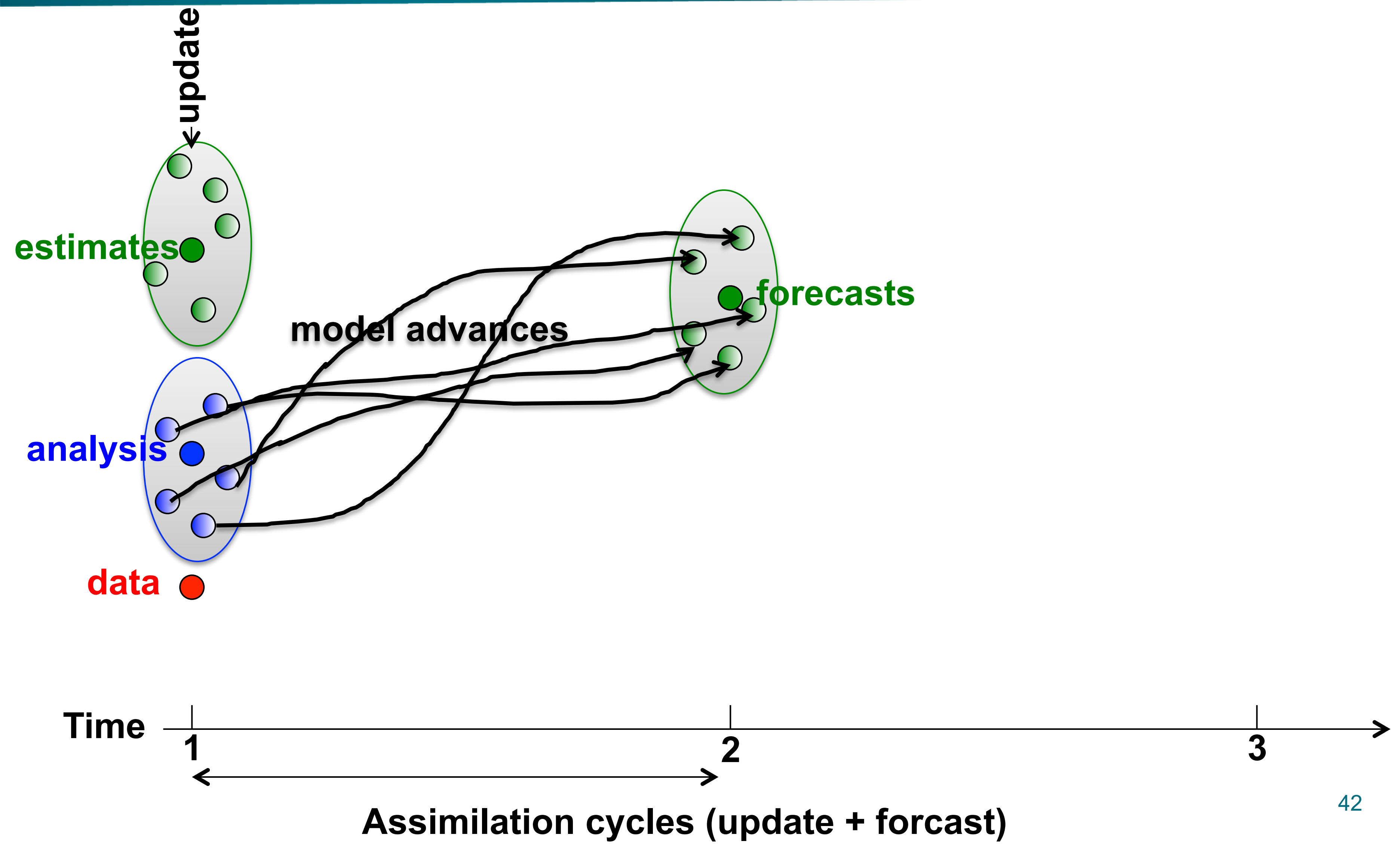

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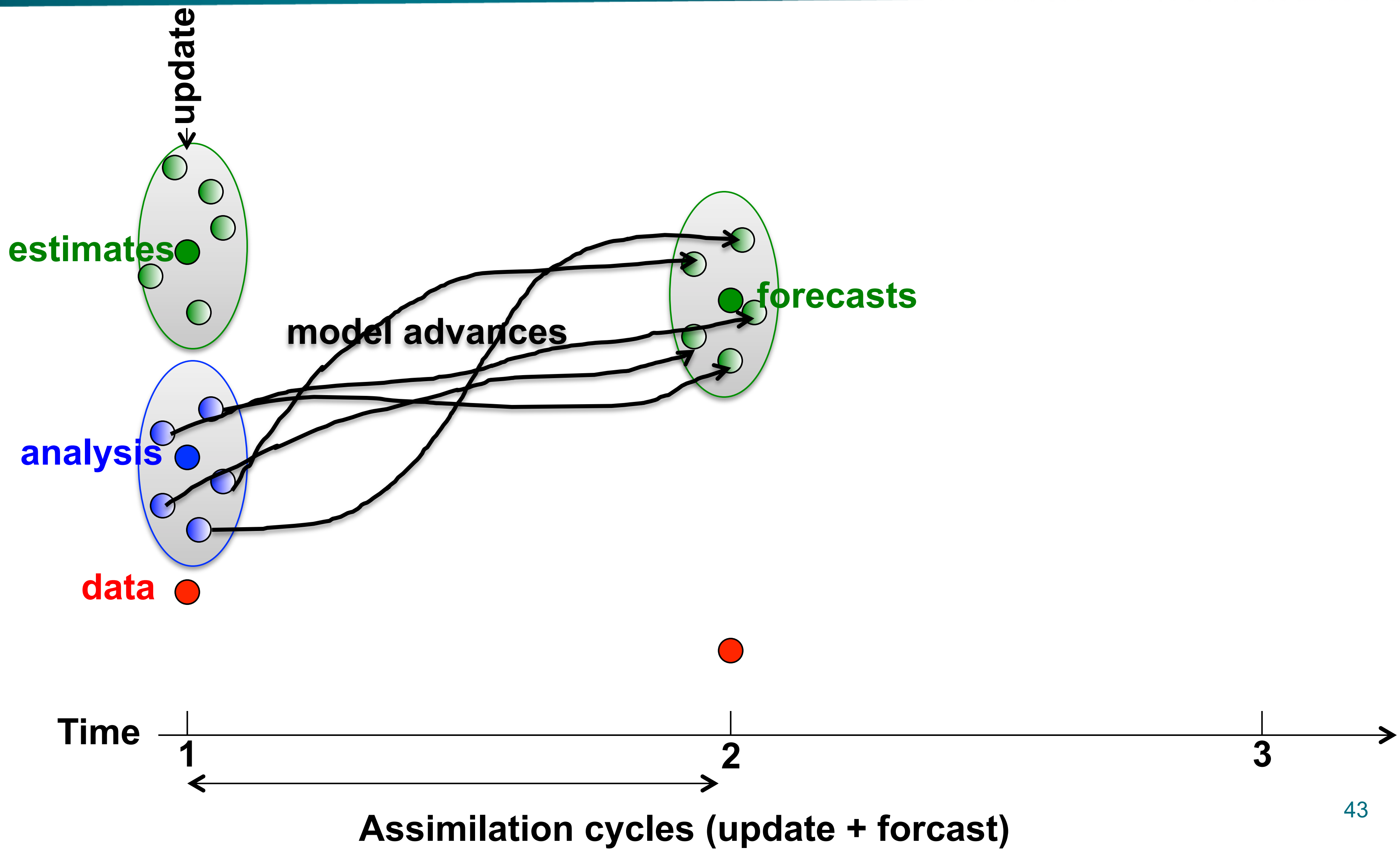

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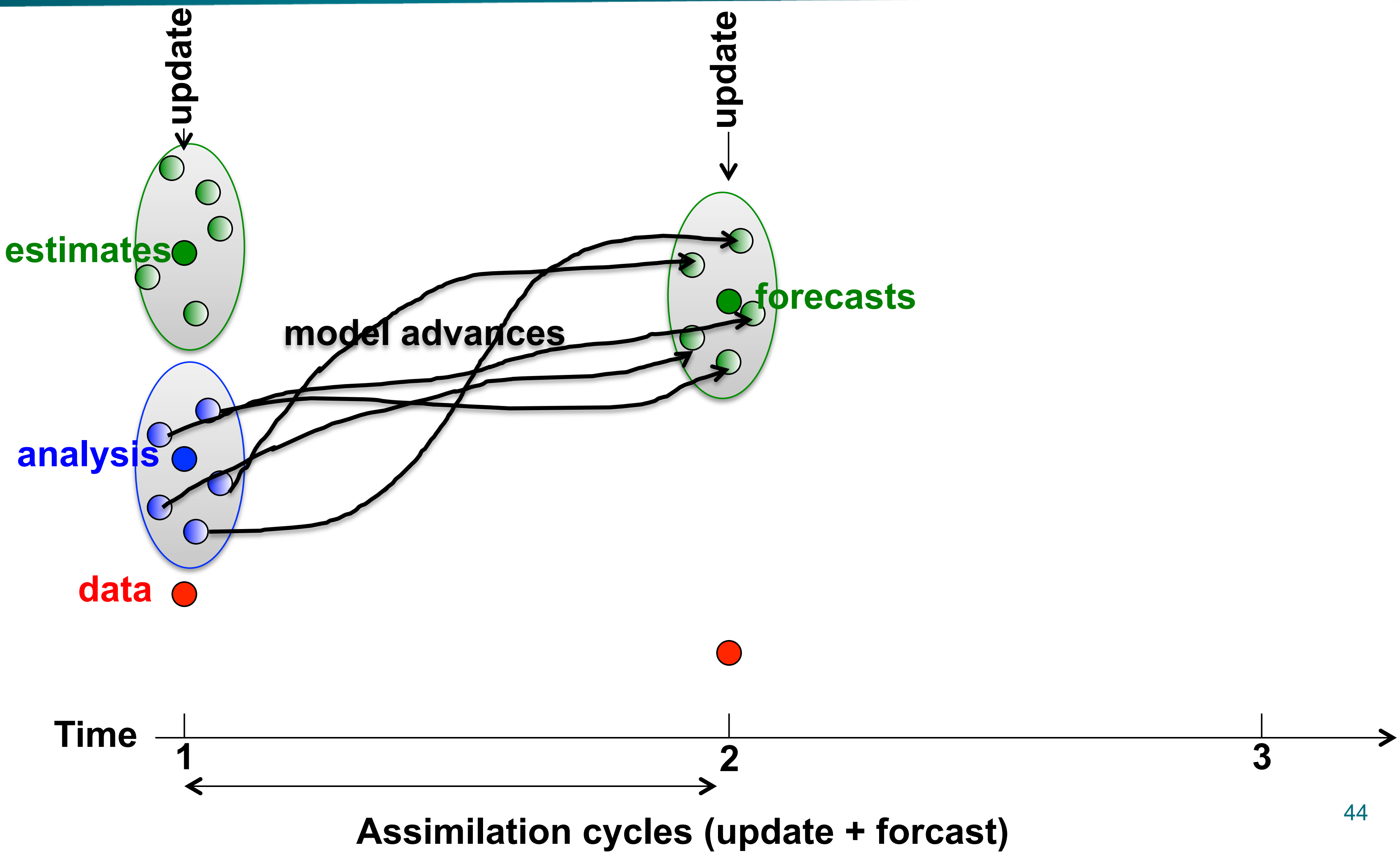

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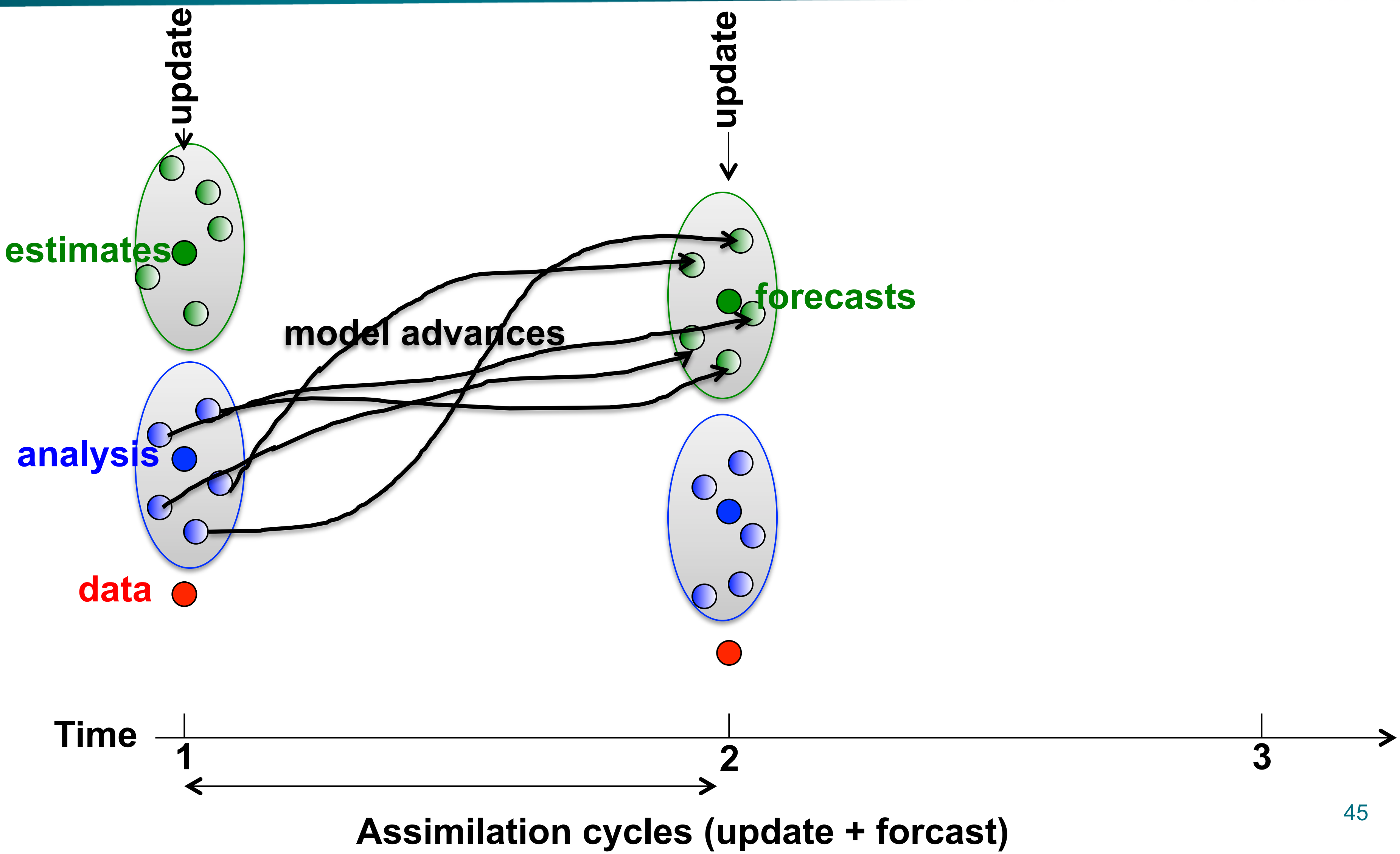

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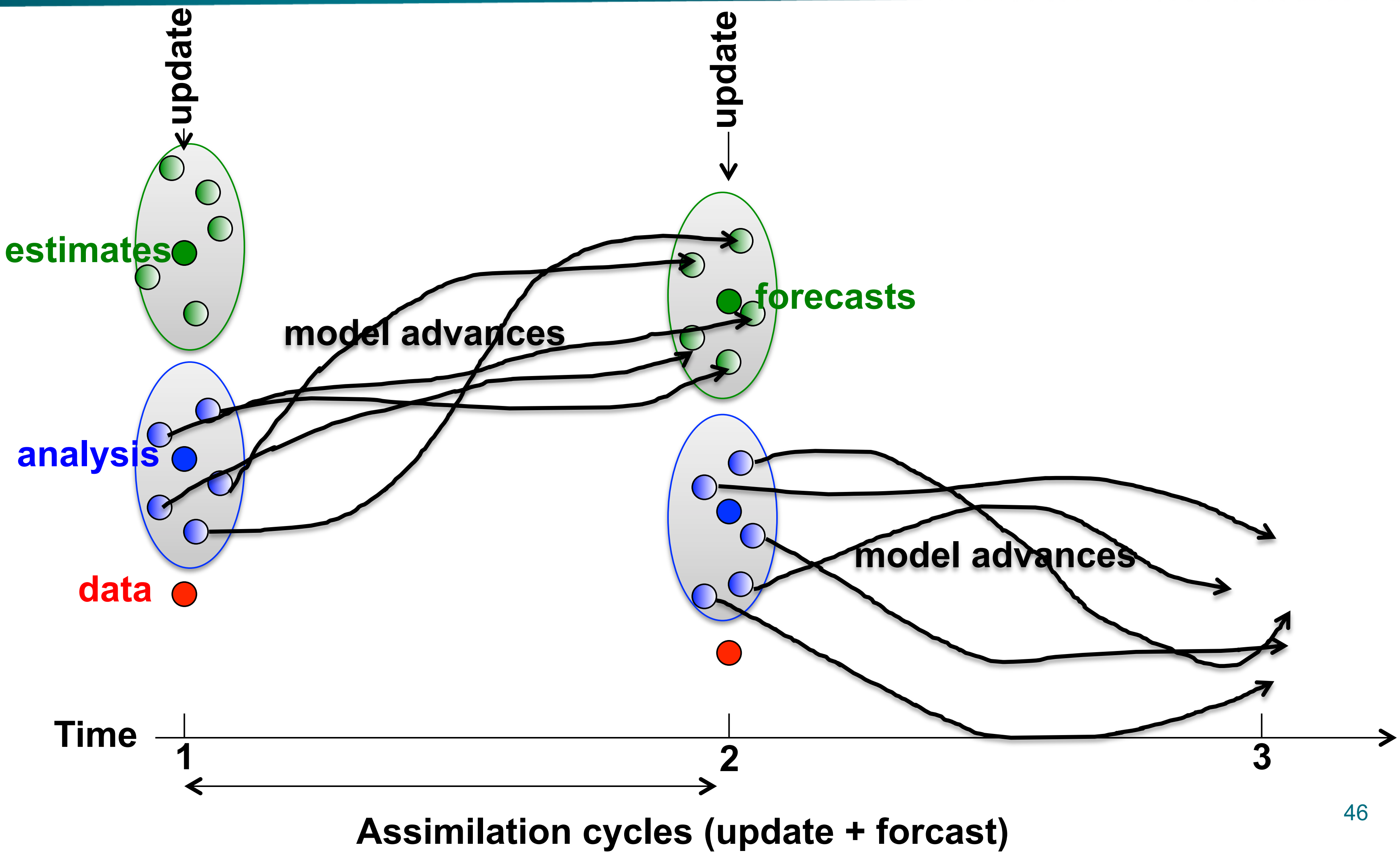

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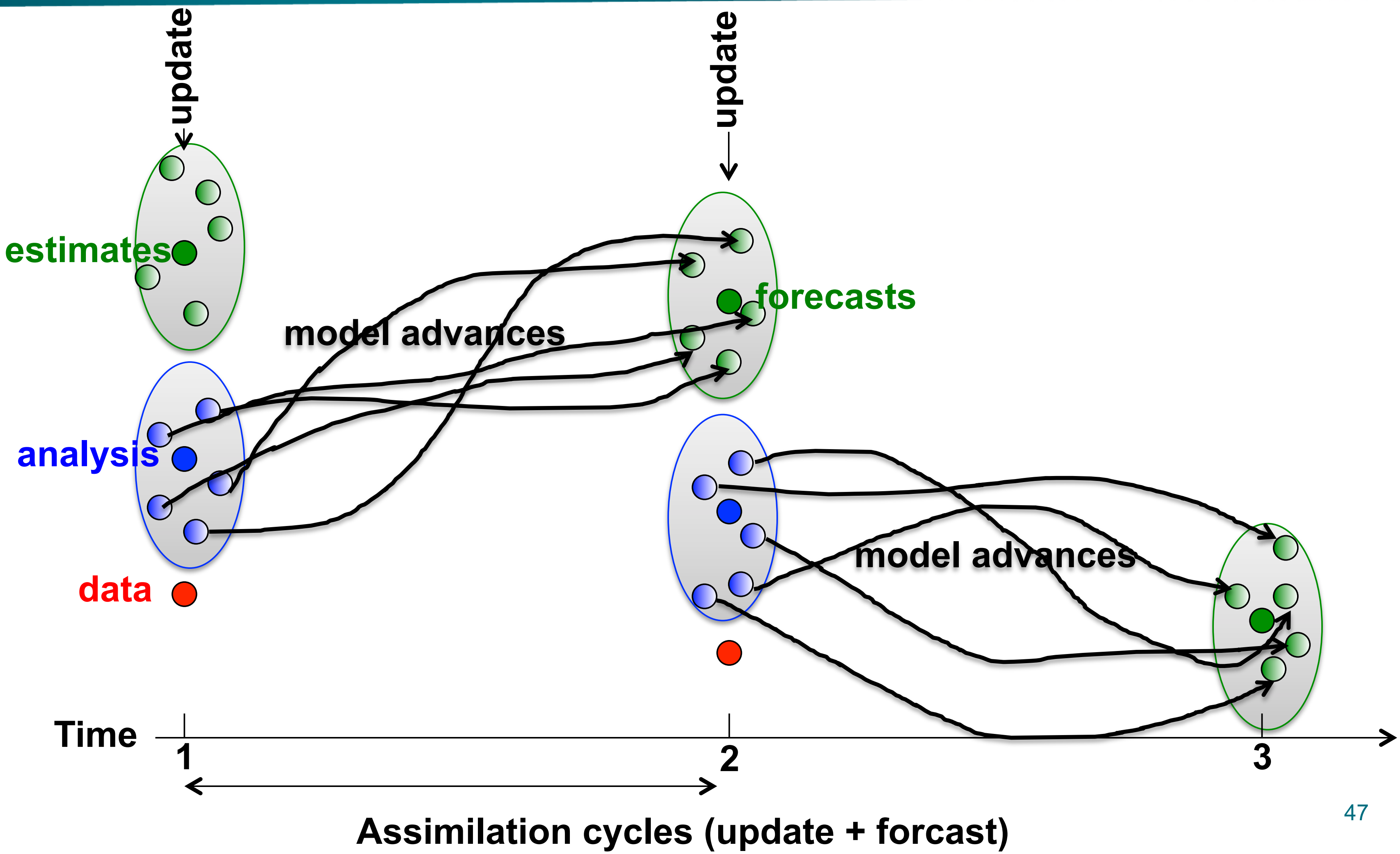

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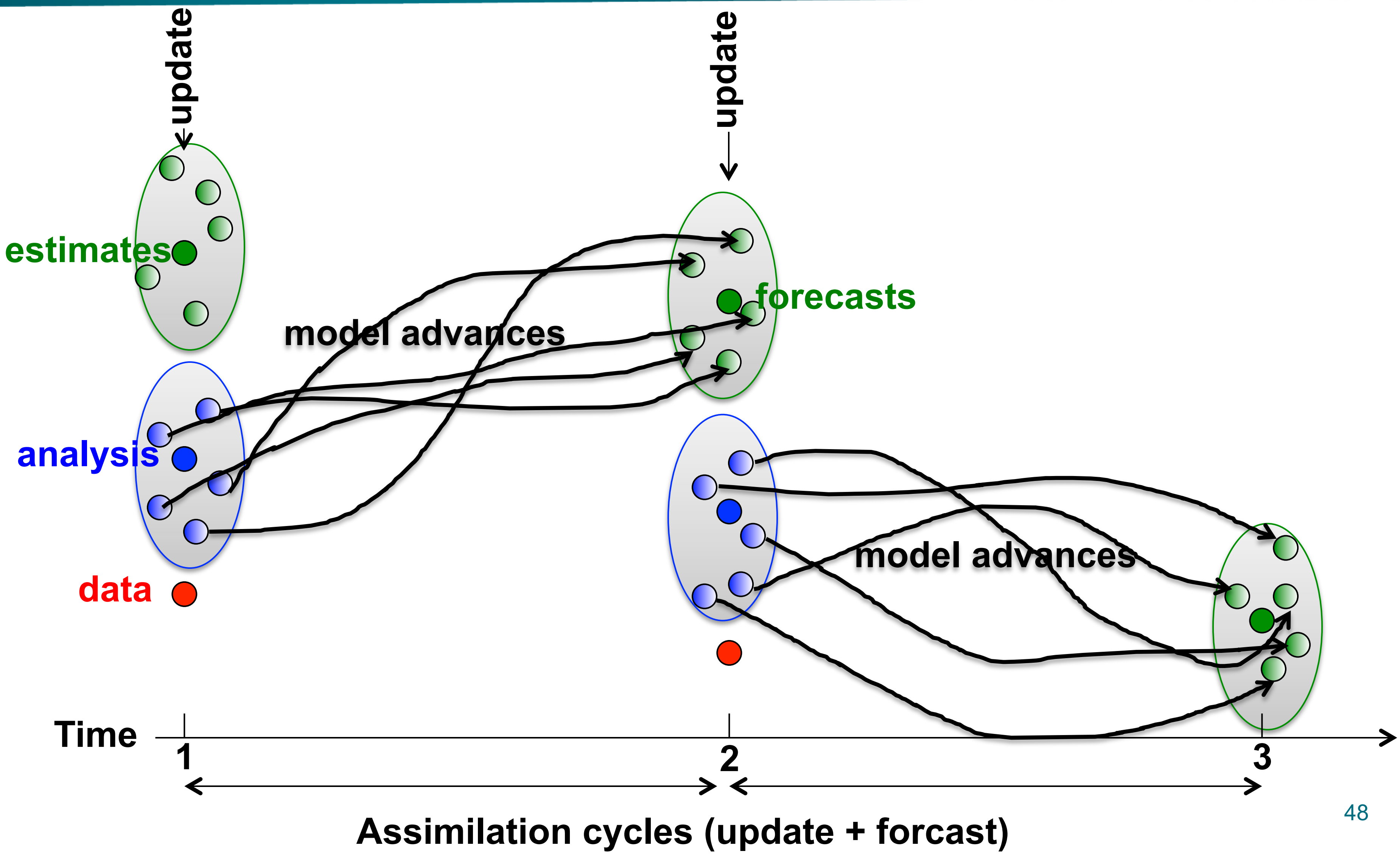

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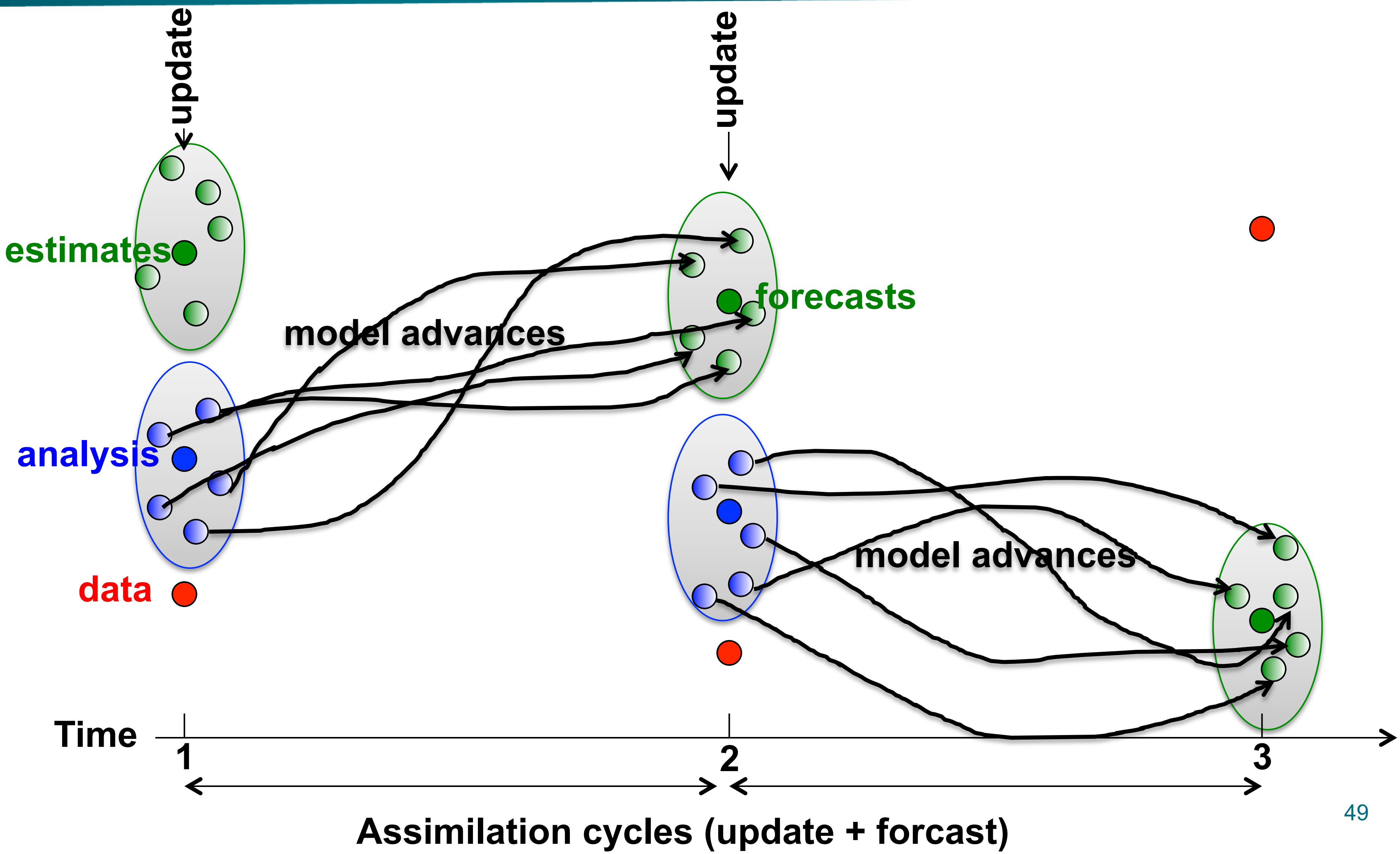

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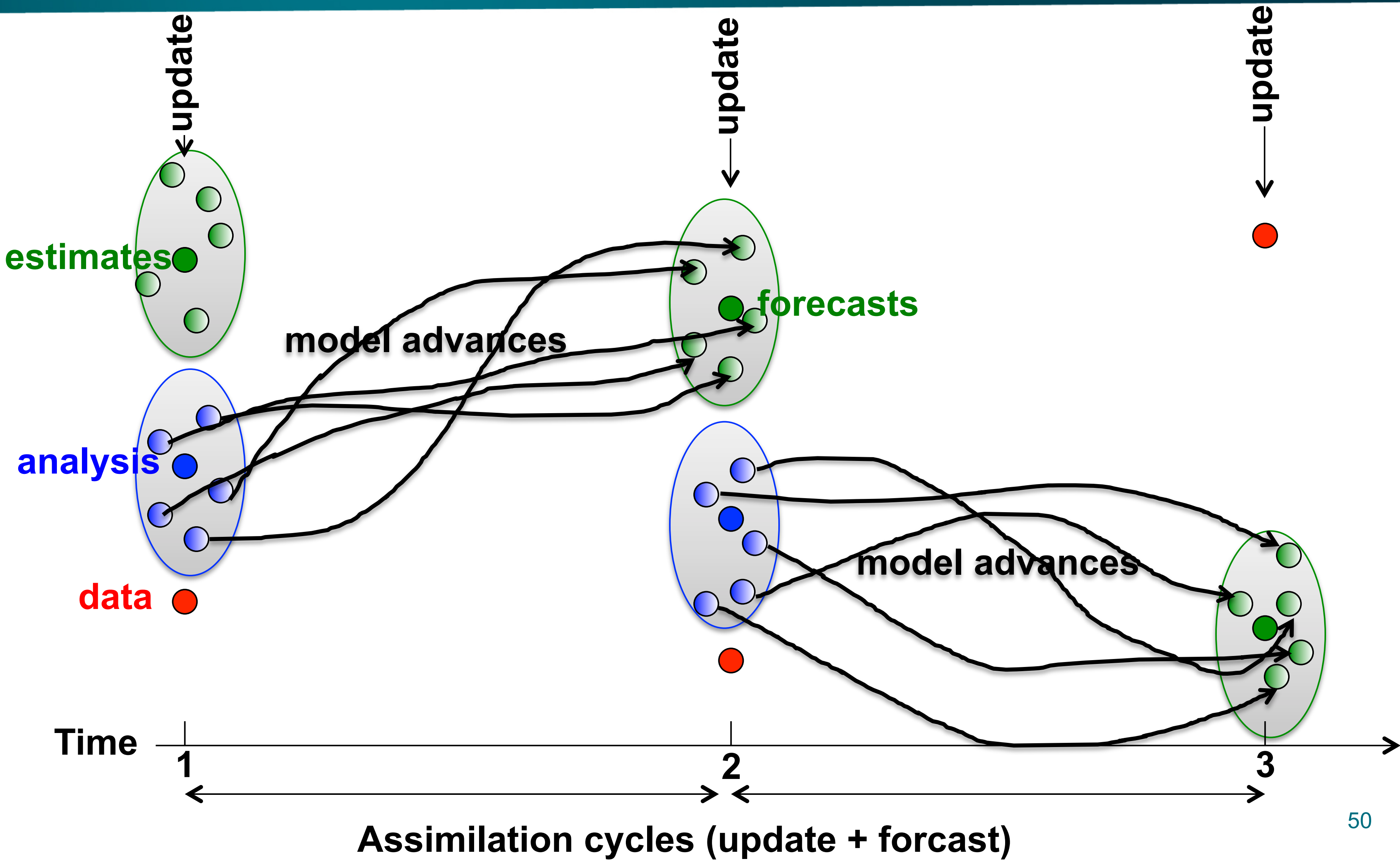

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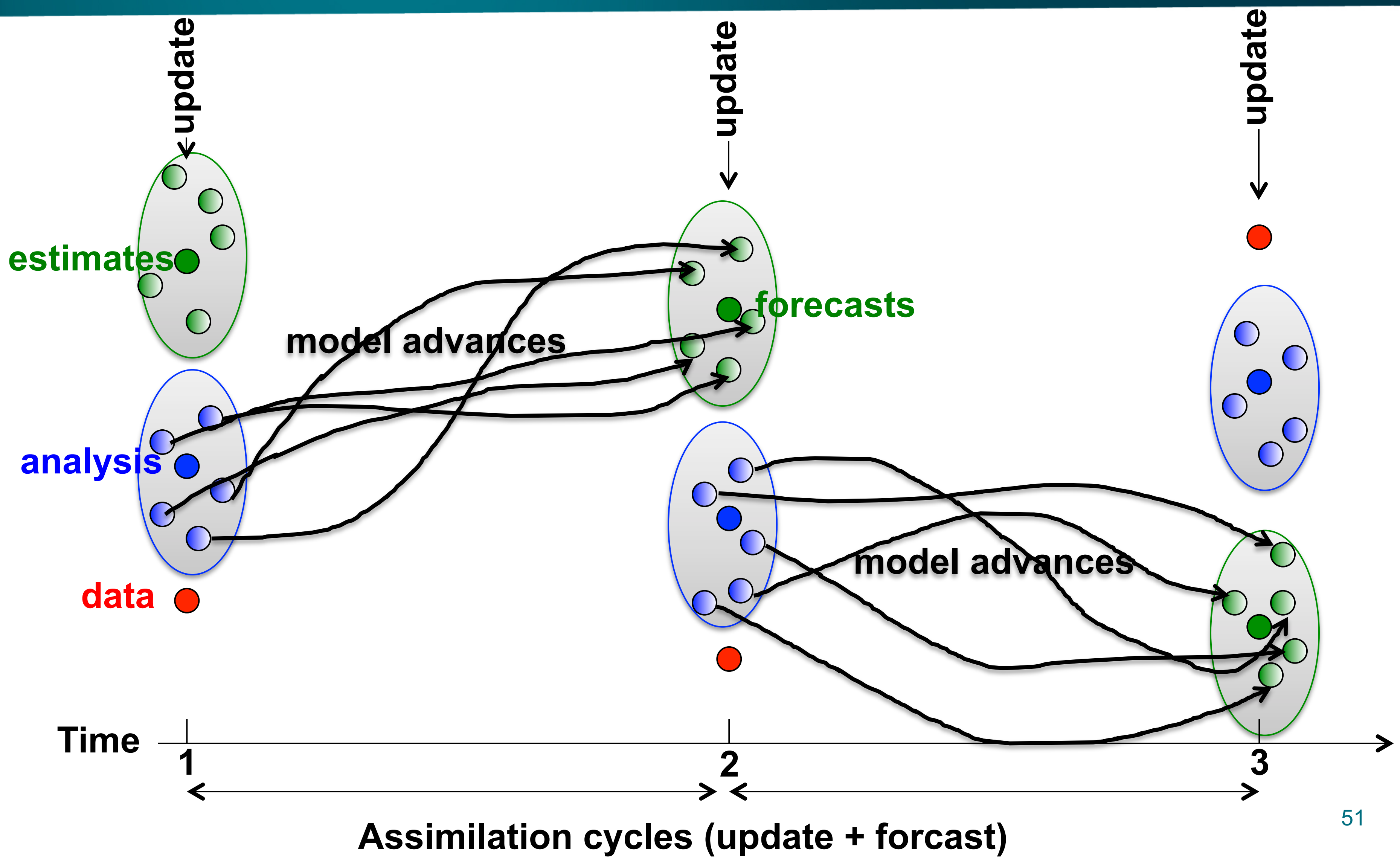

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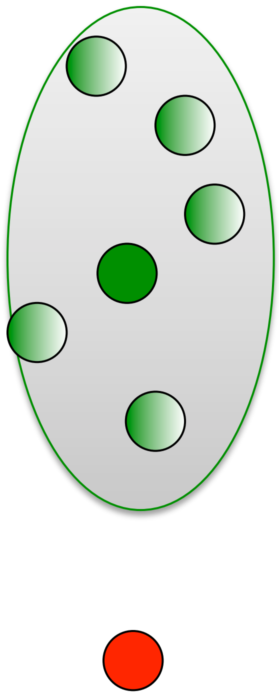
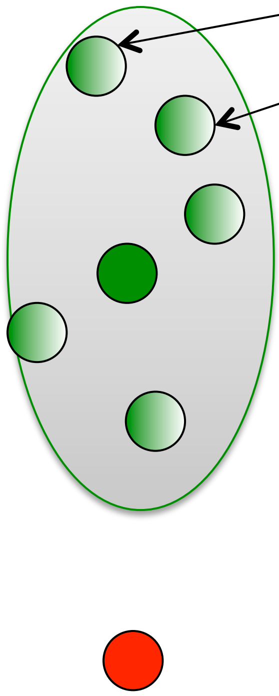


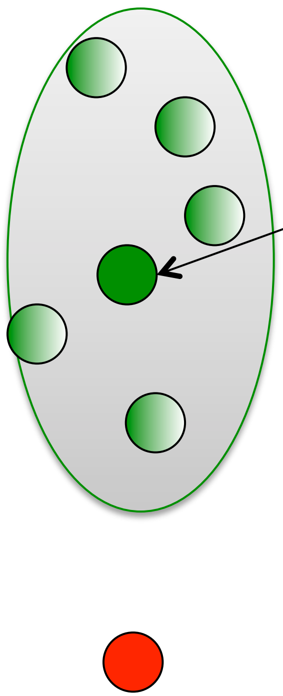
Ensemble data assimilation

$$X = [x_1^f, x_2^f, \dots, x_N^f]$$



Ensemble data assimilation

$$X = [x_1^f, x_2^f, \dots, x_N^f]$$

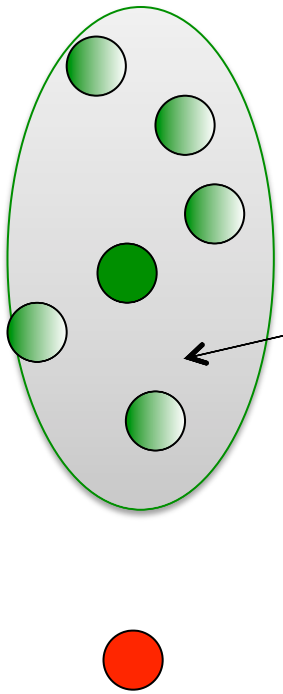


$$\bar{x}^f = \frac{1}{N}\sum_{i=1}^{N} x_i^f$$

Ensemble data assimilation

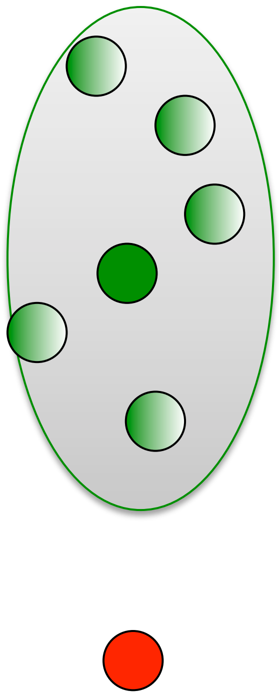
$$X = [x_1^f, x_2^f, \ldots, x_N^f]$$

$$\bar{x}^f = \frac{1}{N}\sum_{i=1}^{N} x_i^f$$



$$X' = X - \bar{x}^f$$

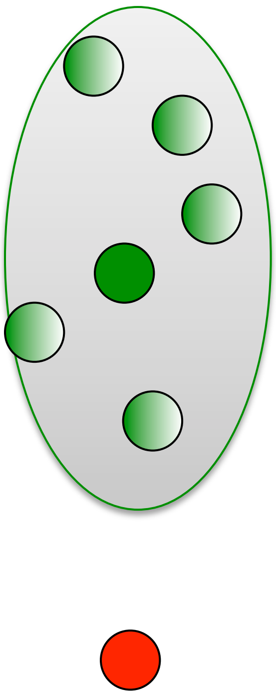
Ensemble data assimilation



$$X' = X - \bar{x}^f$$

$$P^f = \frac{1}{N-1}\left(X' X'^T\right)$$

Ensemble data assimilation



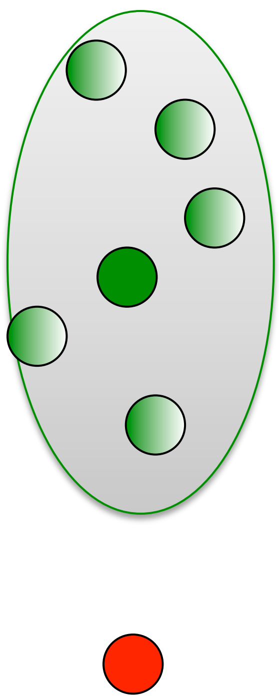
forecast error covariance

$$P^f = \frac{1}{N-1}\left(X' X'^T\right)$$

$$K = P^f H^T \left(H P^f H^T + R\right)$$

observational error covariance

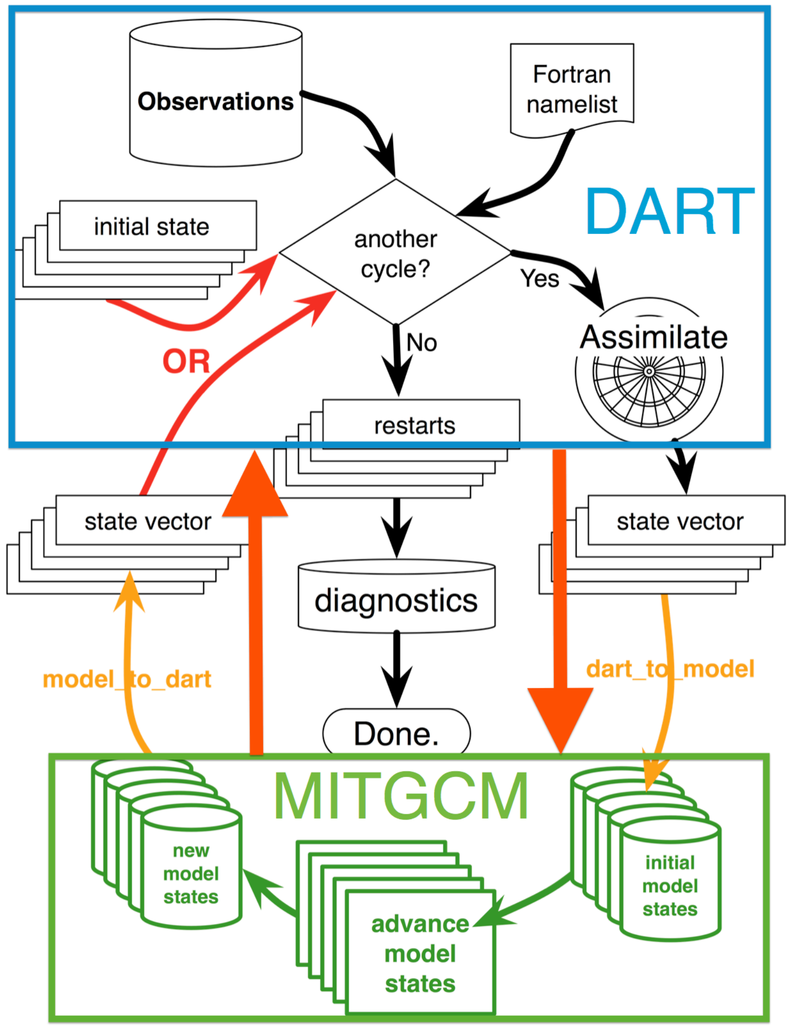
Ensemble data assimilation



$$K = P^f H^T (H P^f H^T + R)$$

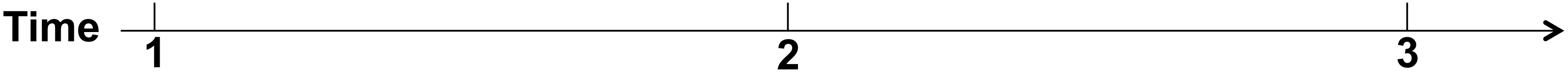
$$x_i^a = x_i^b + K\,(y^o - h(x_i^b))$$

DART-MITgcm

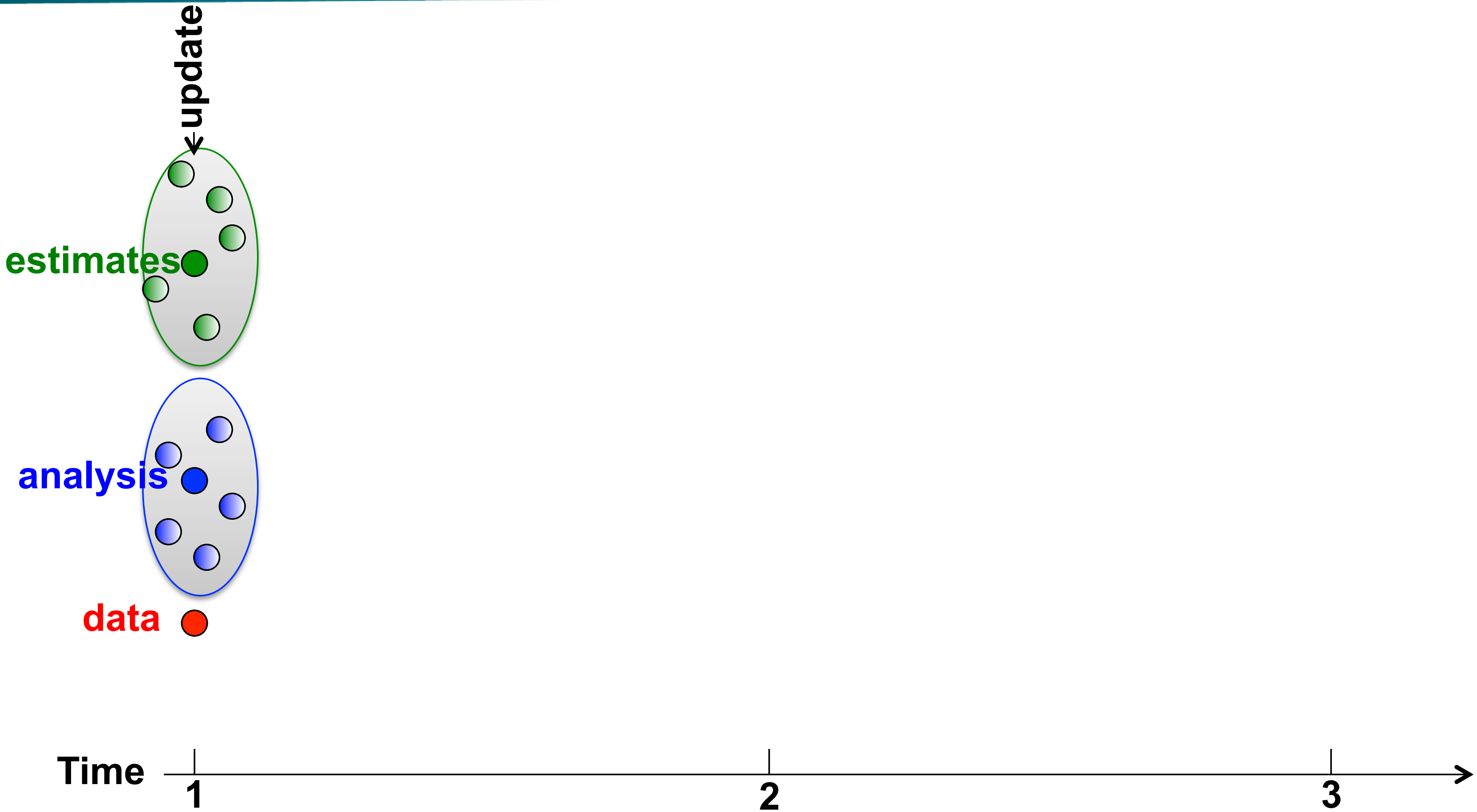


http://www.image.ucar.edu/DAReS/DART/index.php

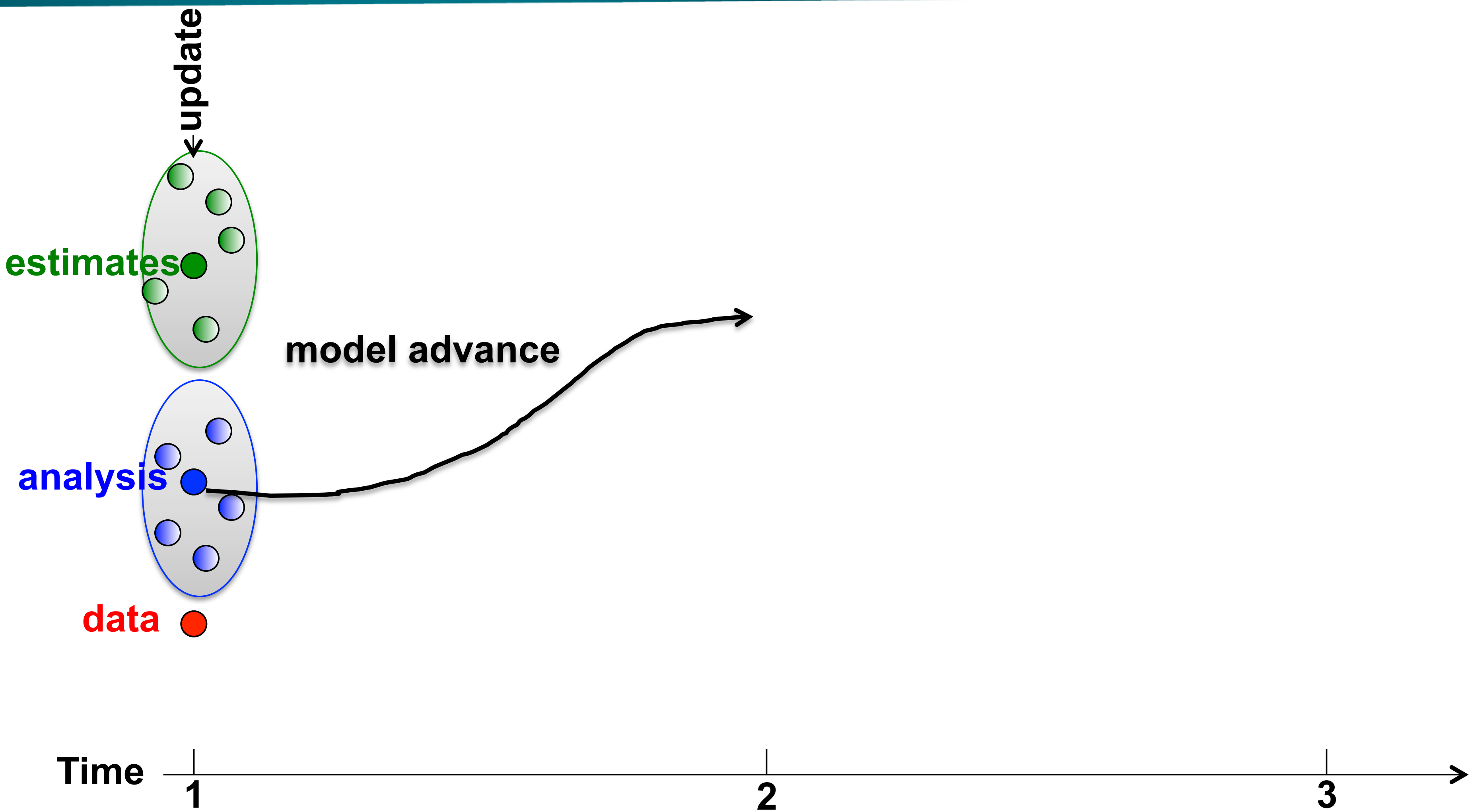
EnOI principle



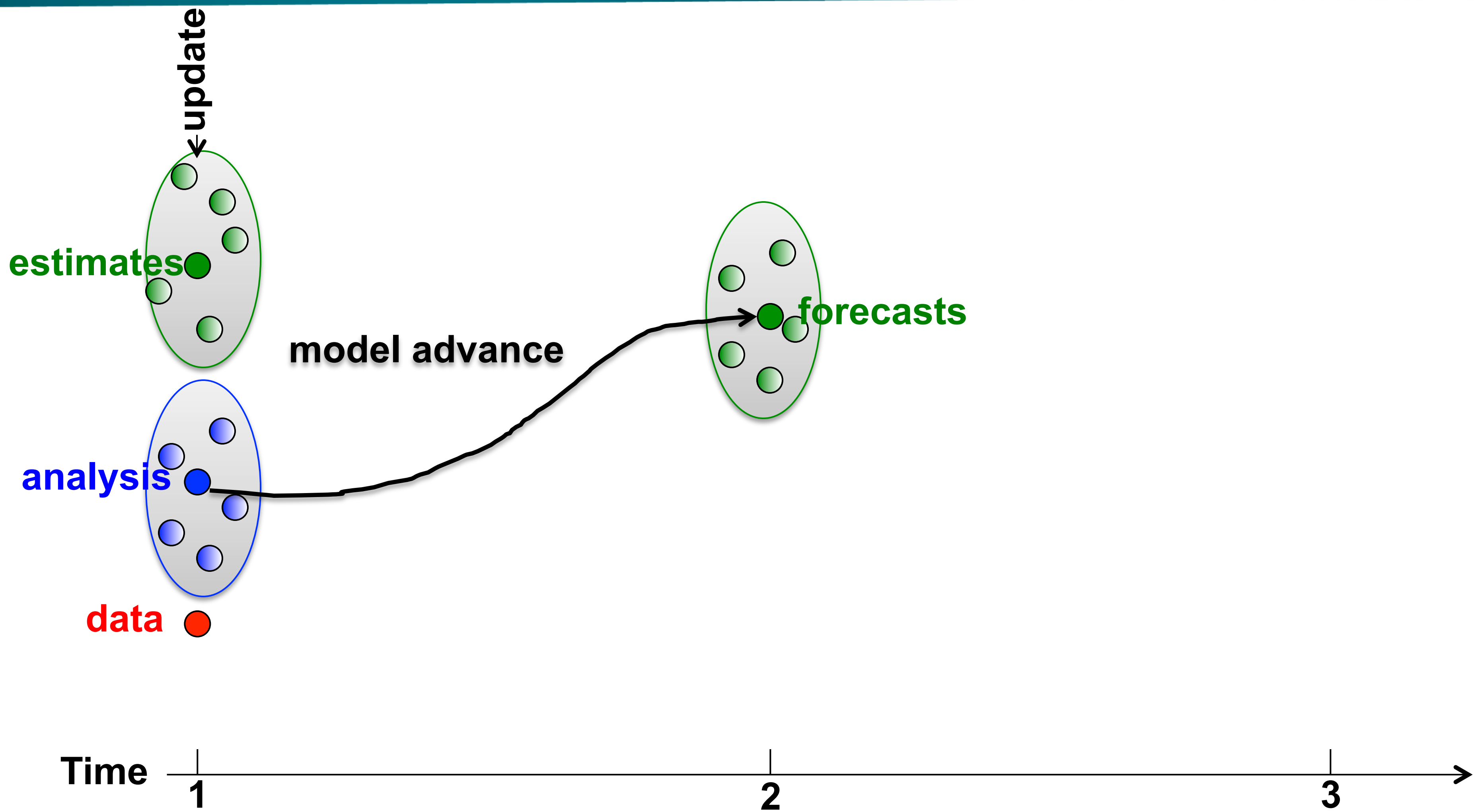
EnOI principle



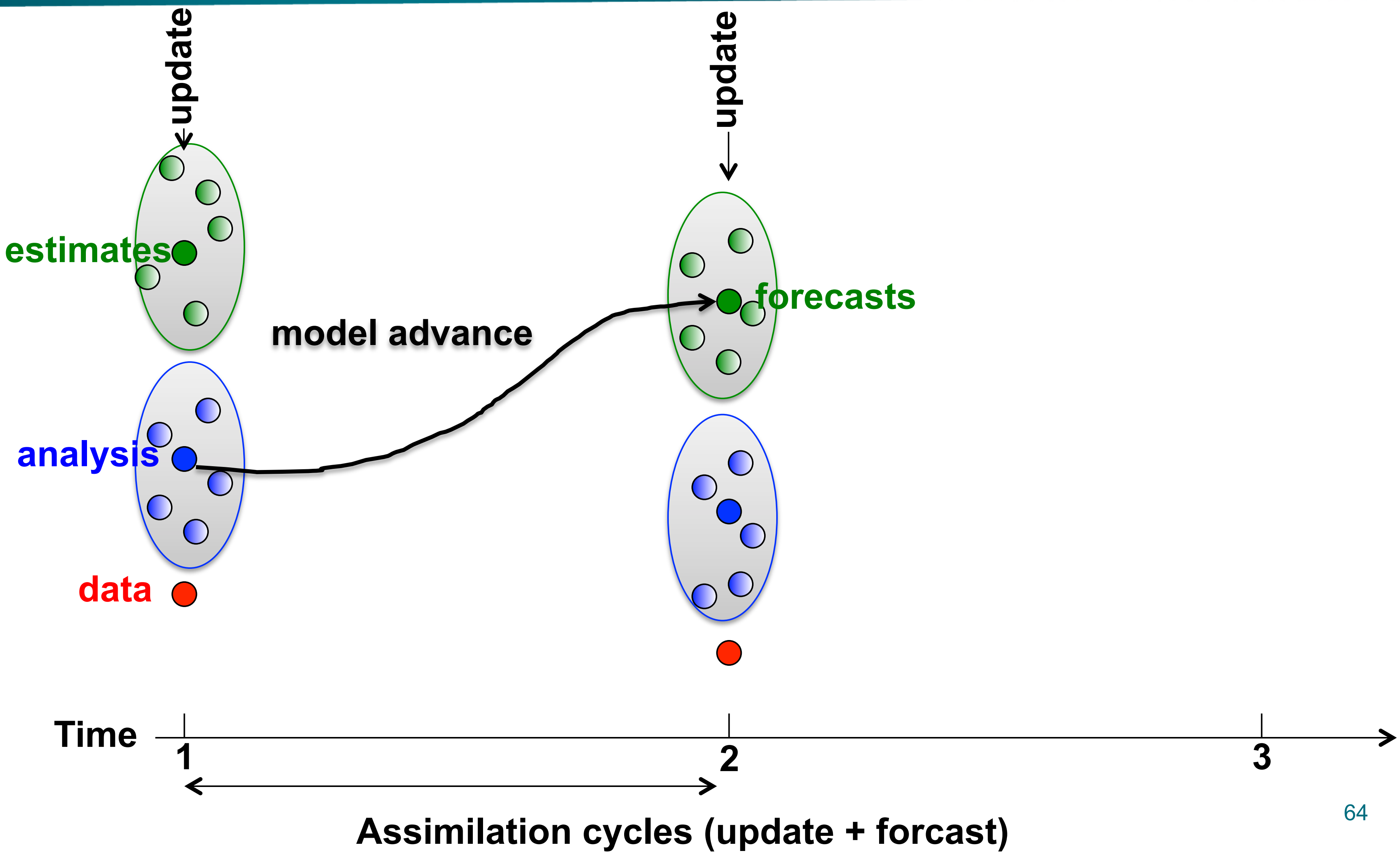
EnOI principle



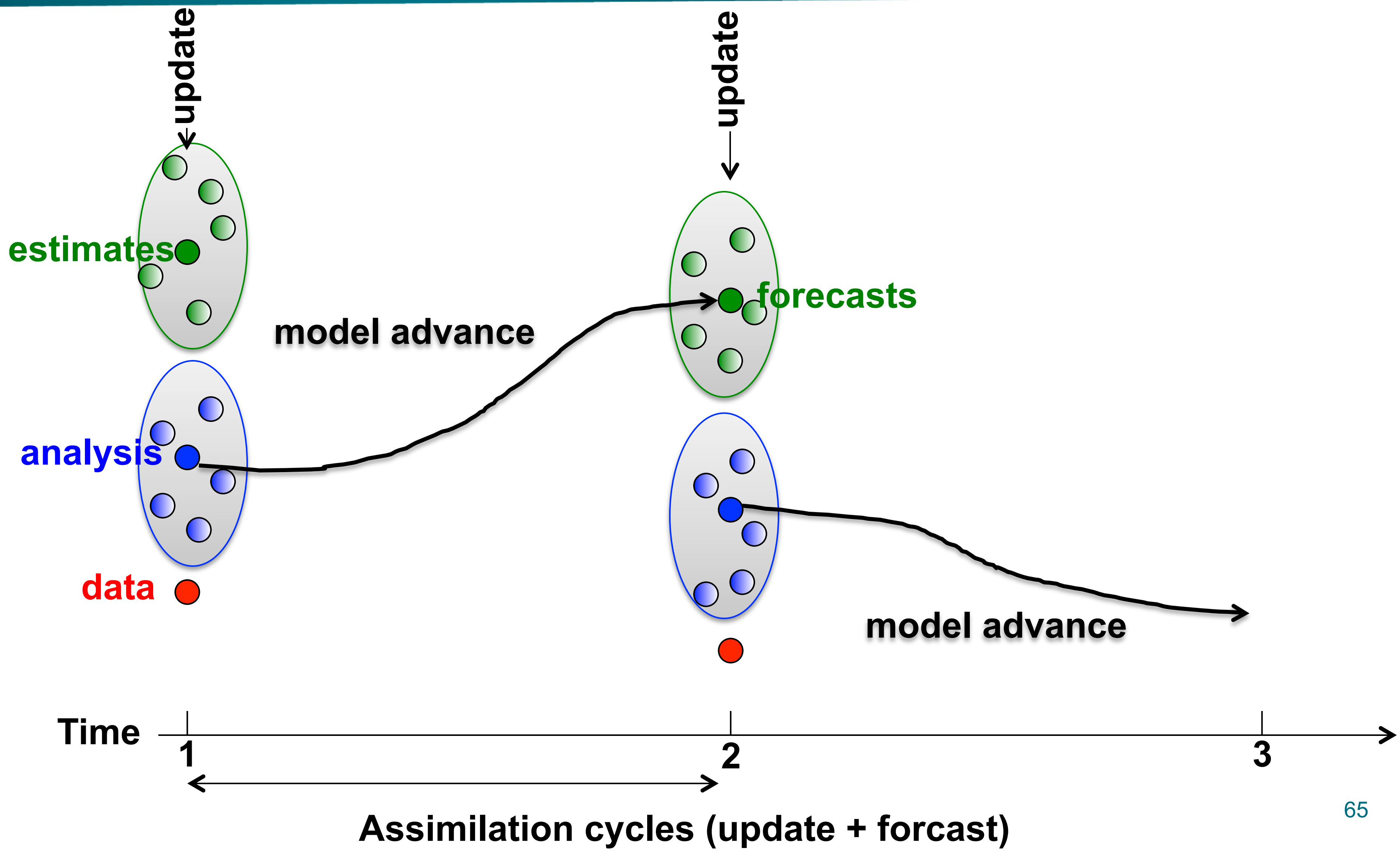
EnOI principle



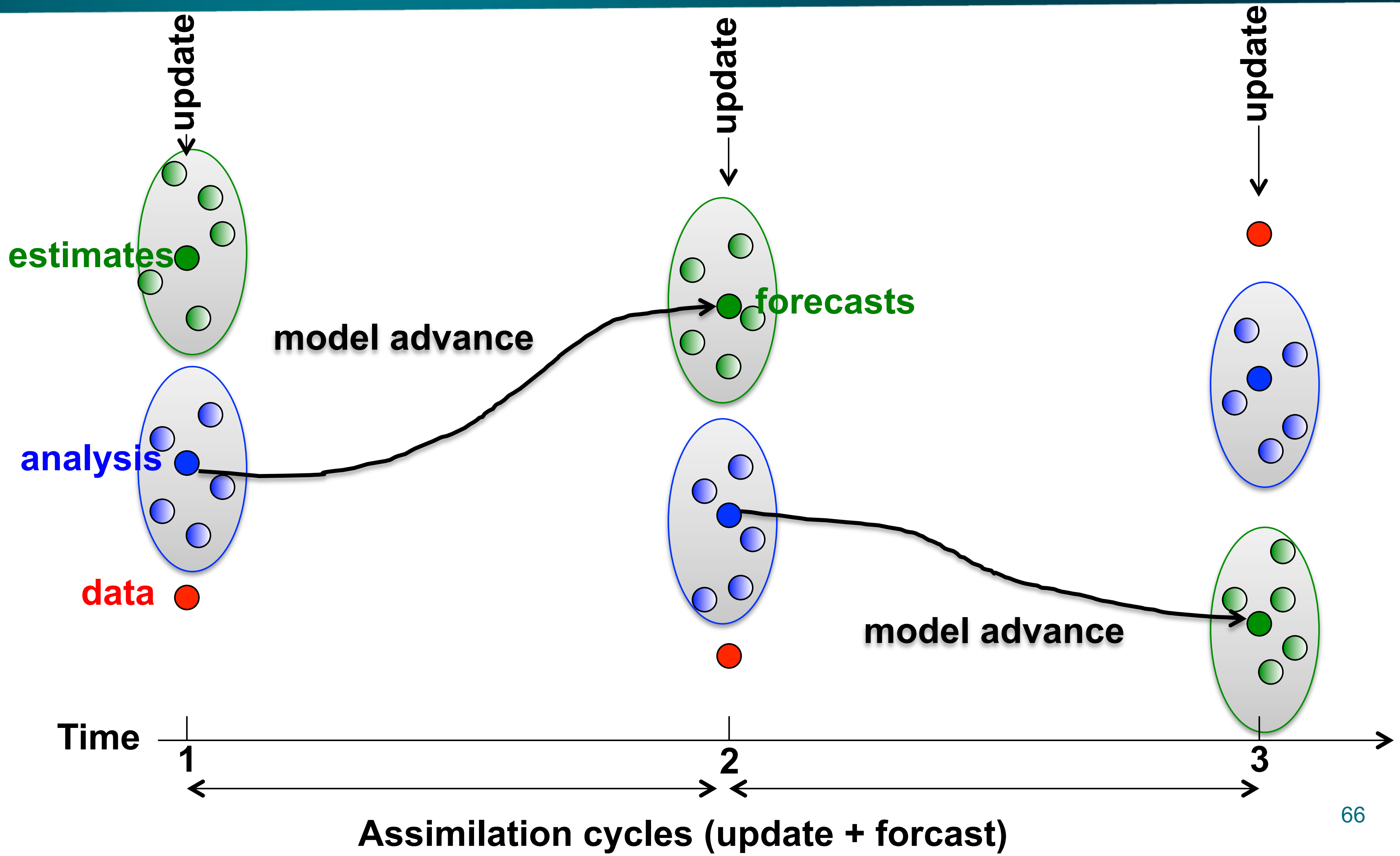
EnOI principle



EnOI principle

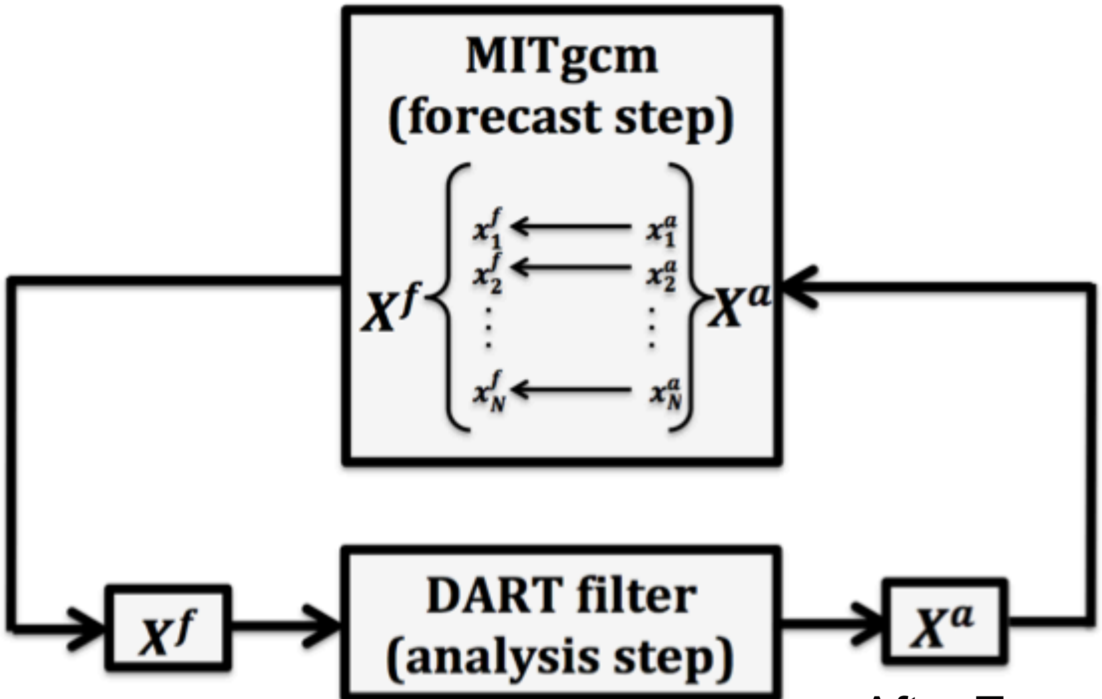


EnOI principle



EnOI

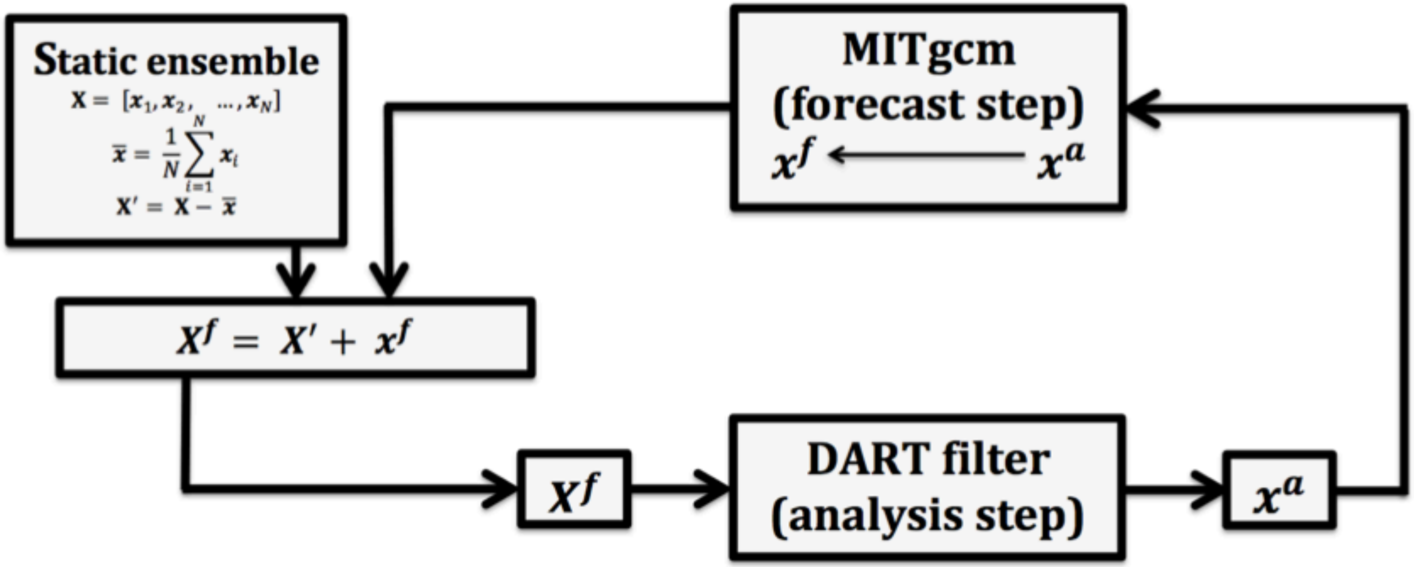
EnOI



After Toye et al. 2017

In the EnKF configuration, all the members are advanced by the model.

EnOI



After Toye et al. 2017

- With the EnOI, only the analysis is forecasted
- Reduce the cost of the EnKF forecast step by a factor N
- The forecast ensemble needed in the analysis step is built by adding preselected static anomalies to the forecast

Seasonal EnOI

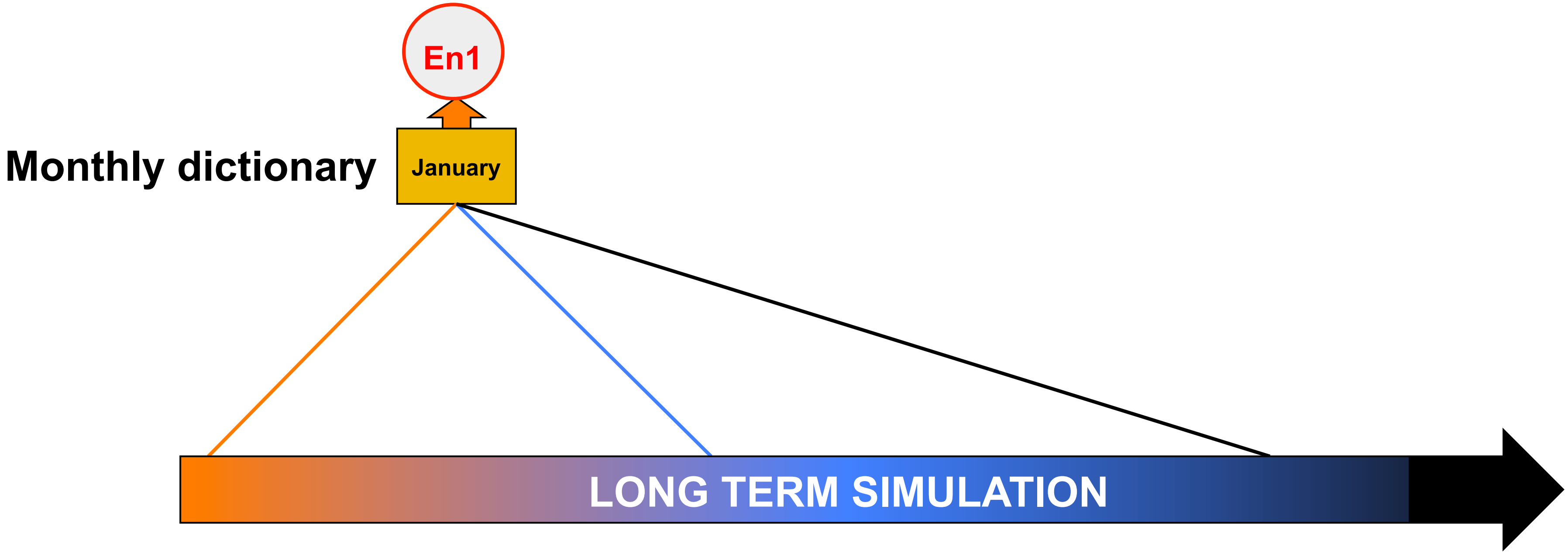
Seasonal EnOI

LONG TERM SIMULATION

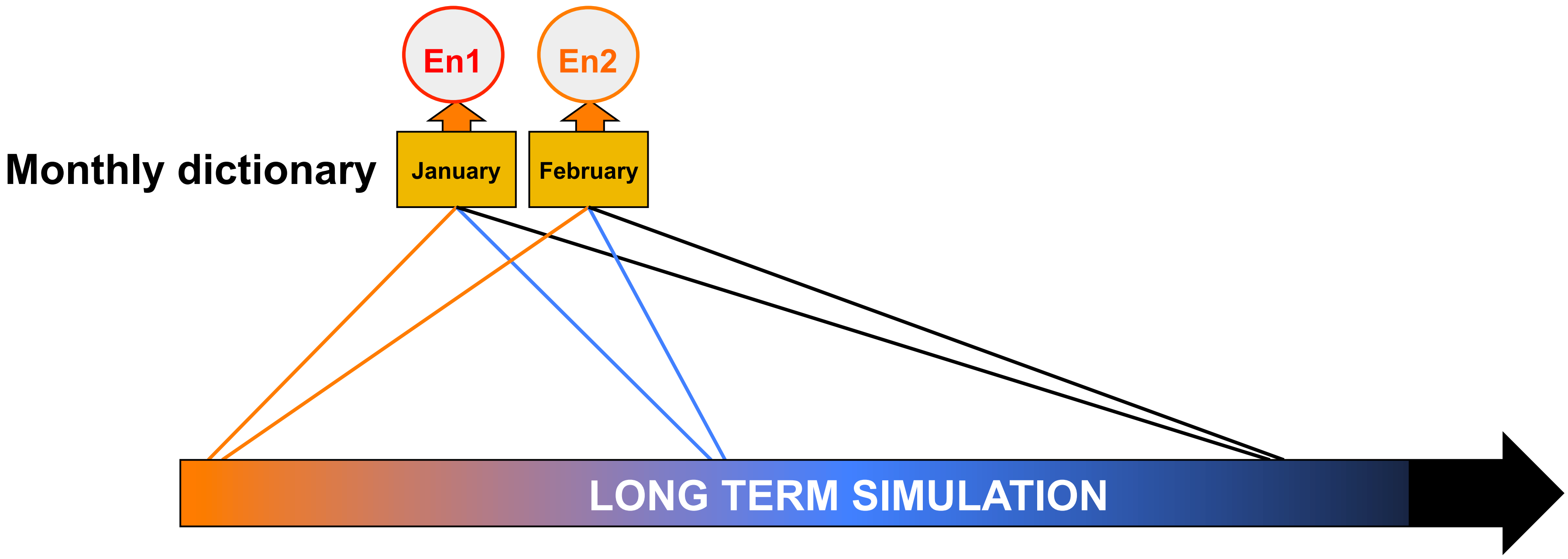
Seasonal EnOI

Monthly dictionary

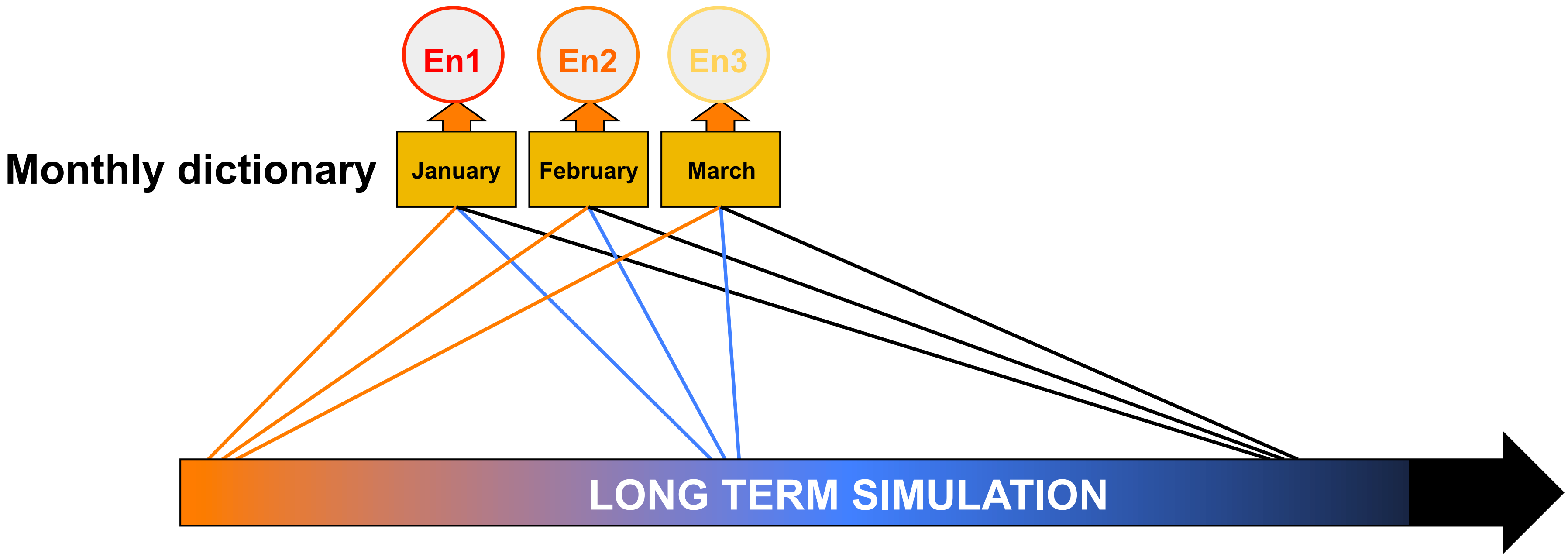
Seasonal EnOI



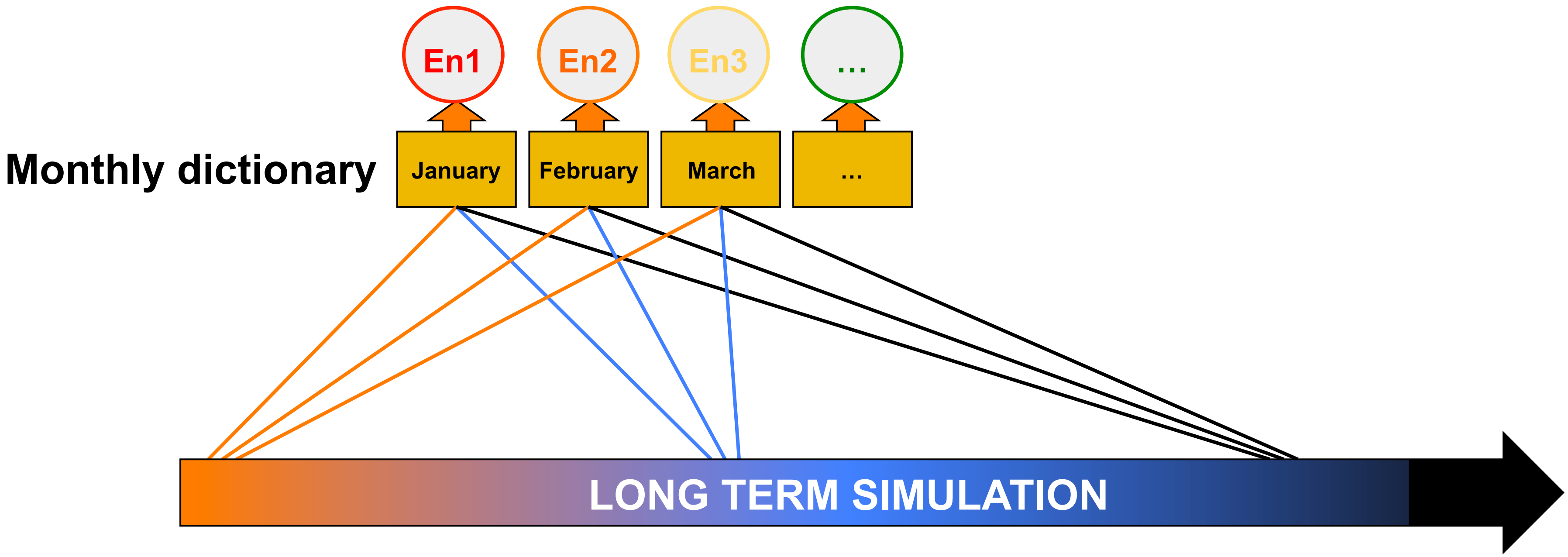
Seasonal EnOI



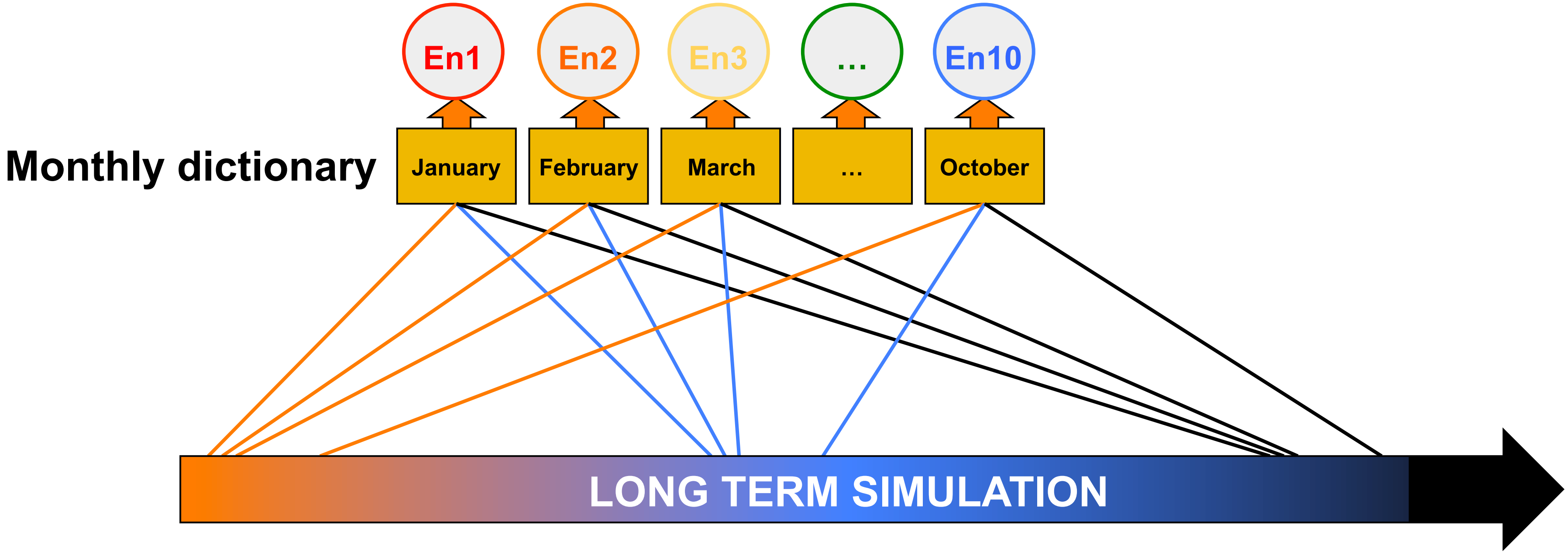
Seasonal EnOI



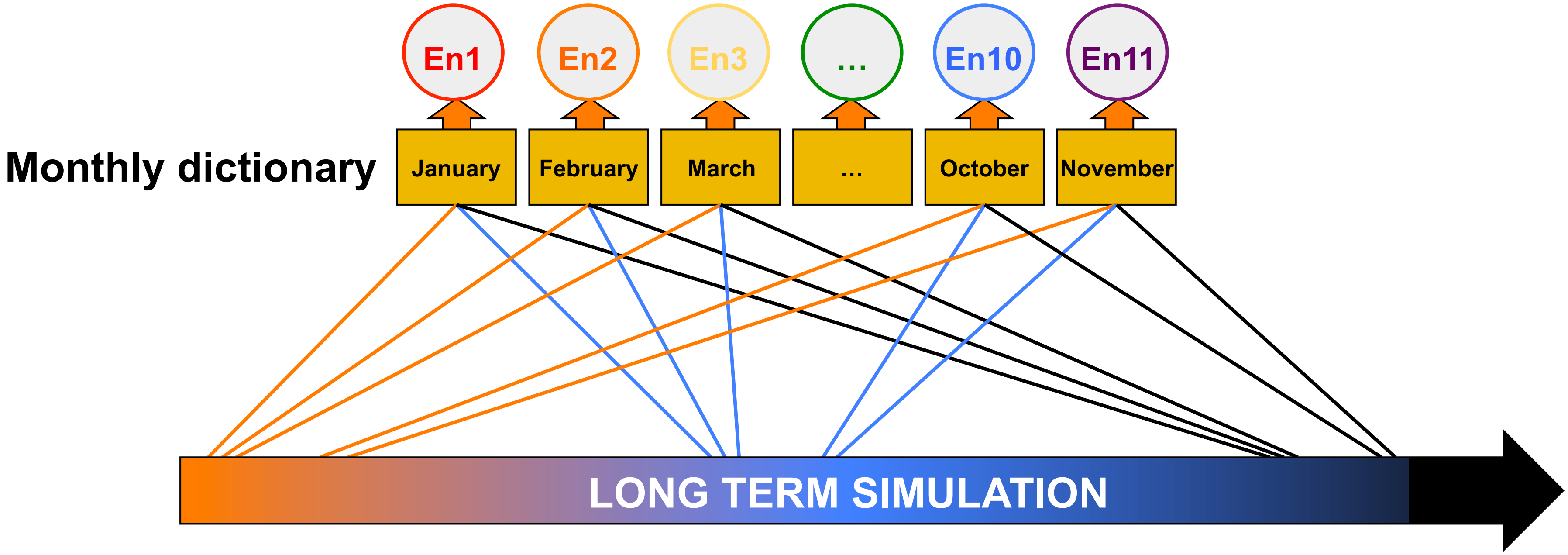
Seasonal EnOI



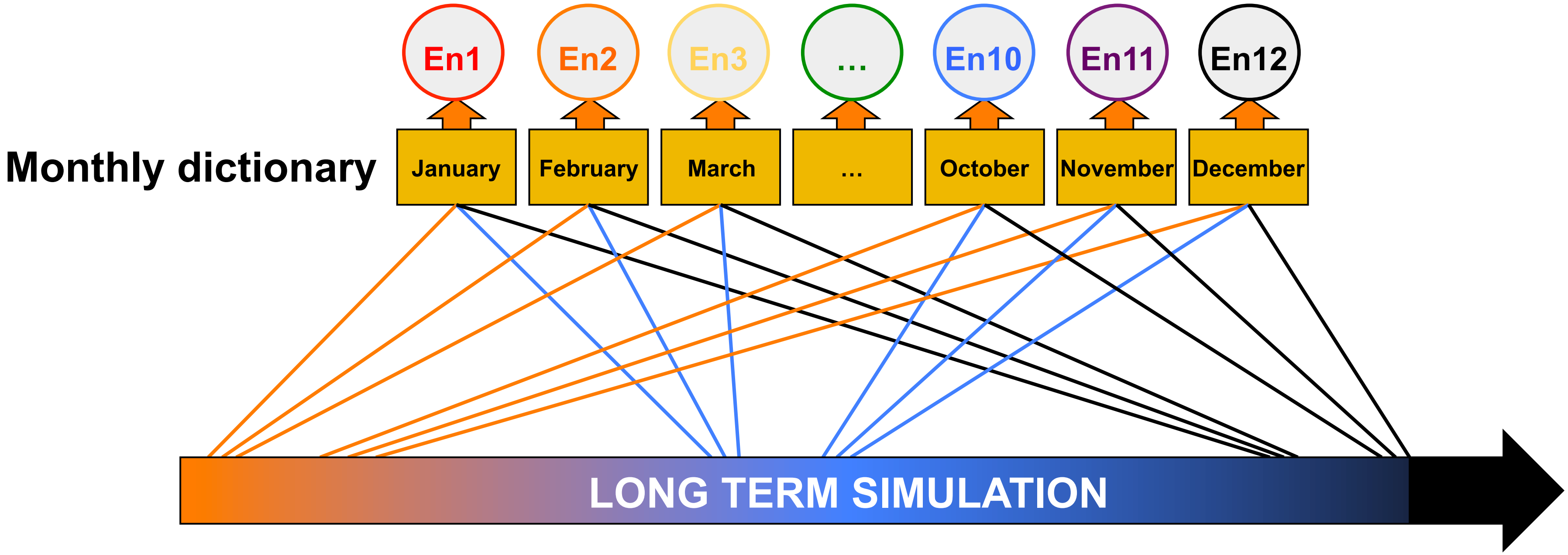
Seasonal EnOI



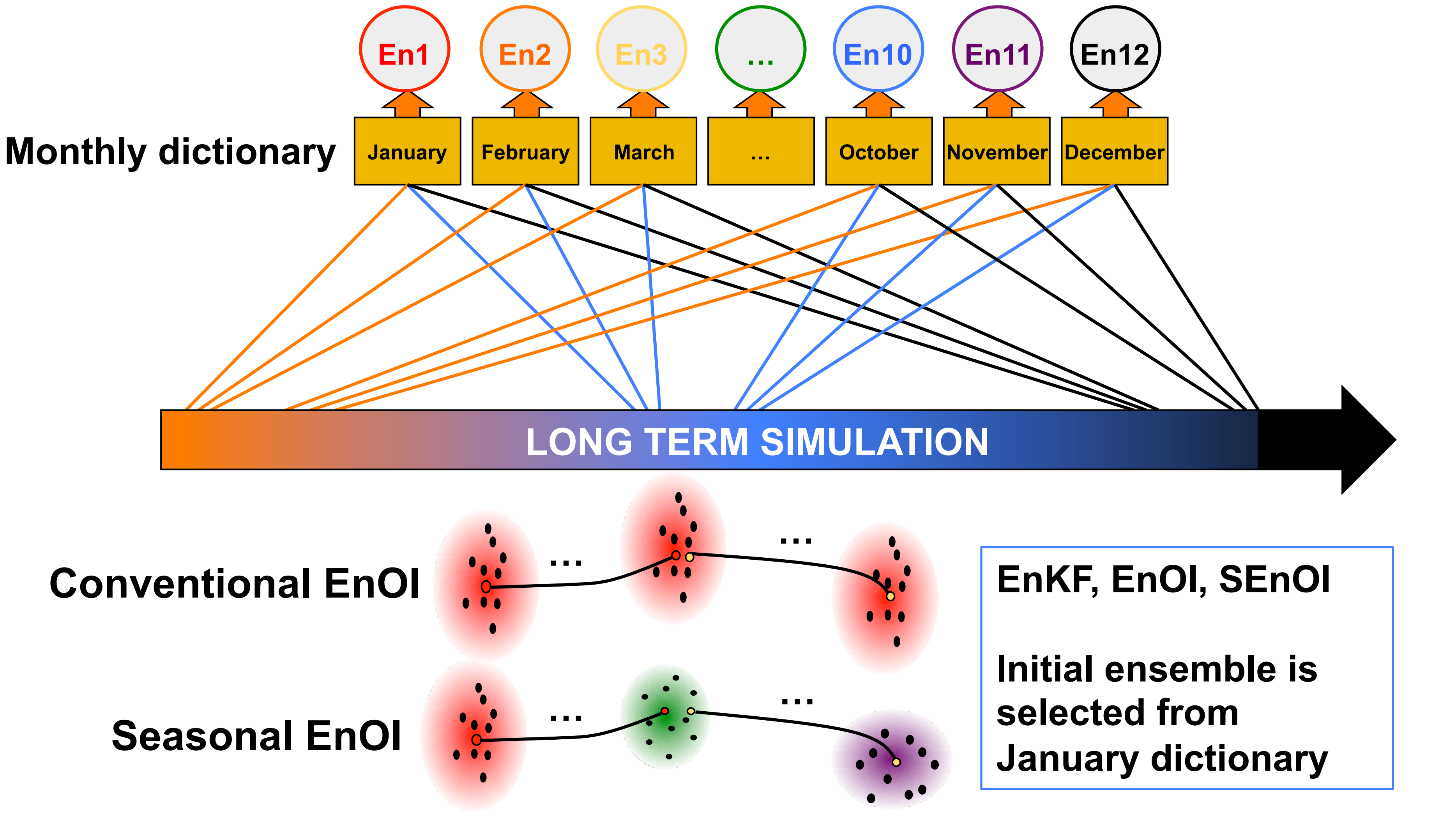
Seasonal EnOI



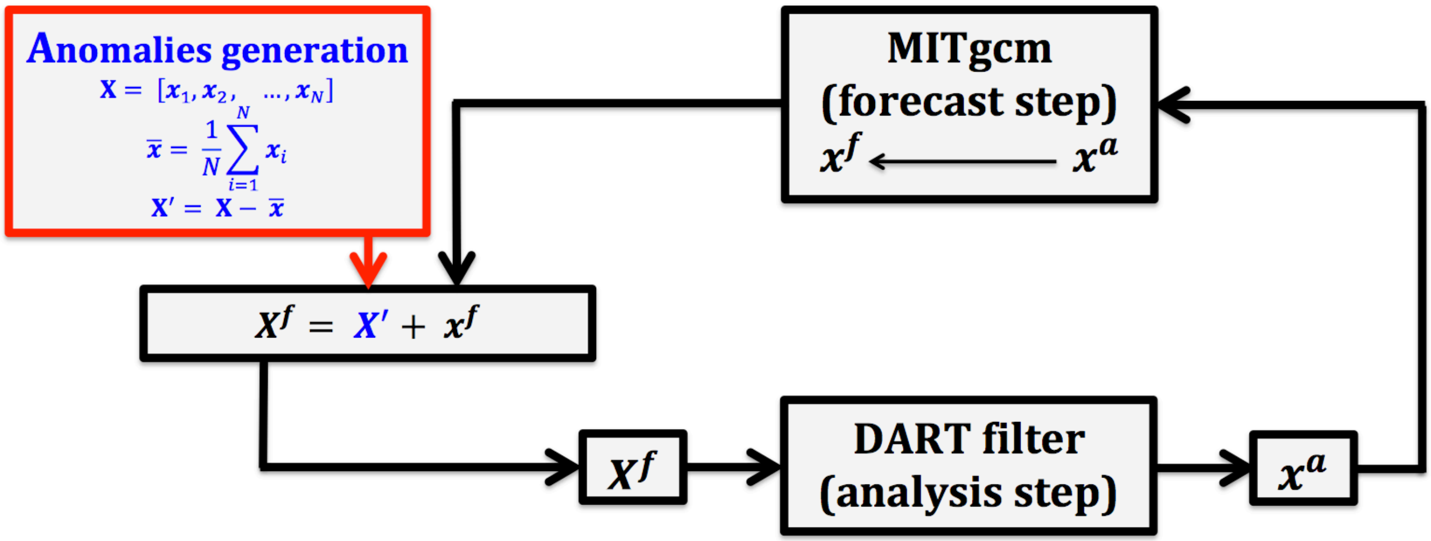
Seasonal EnOI



Seasonal EnOI



Adaptive EnOI



Dynamic update of the anomalies for each assimilation cycle, while keeping only 1 forecast member at the forecast step

Adaptive EnOI – selection algorithm

Adaptive EnOI – selection algorithm

1. Inputs:
   - A dictionary $\mathbf{D} = [\mathbf{d}_1, \mathbf{d}_2, \ldots, \mathbf{d}_L]$ of model outputs
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Adaptive EnOI – selection methods

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- Through correlations:

    Keep the most correlated members with the forecast

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- Through correlations:

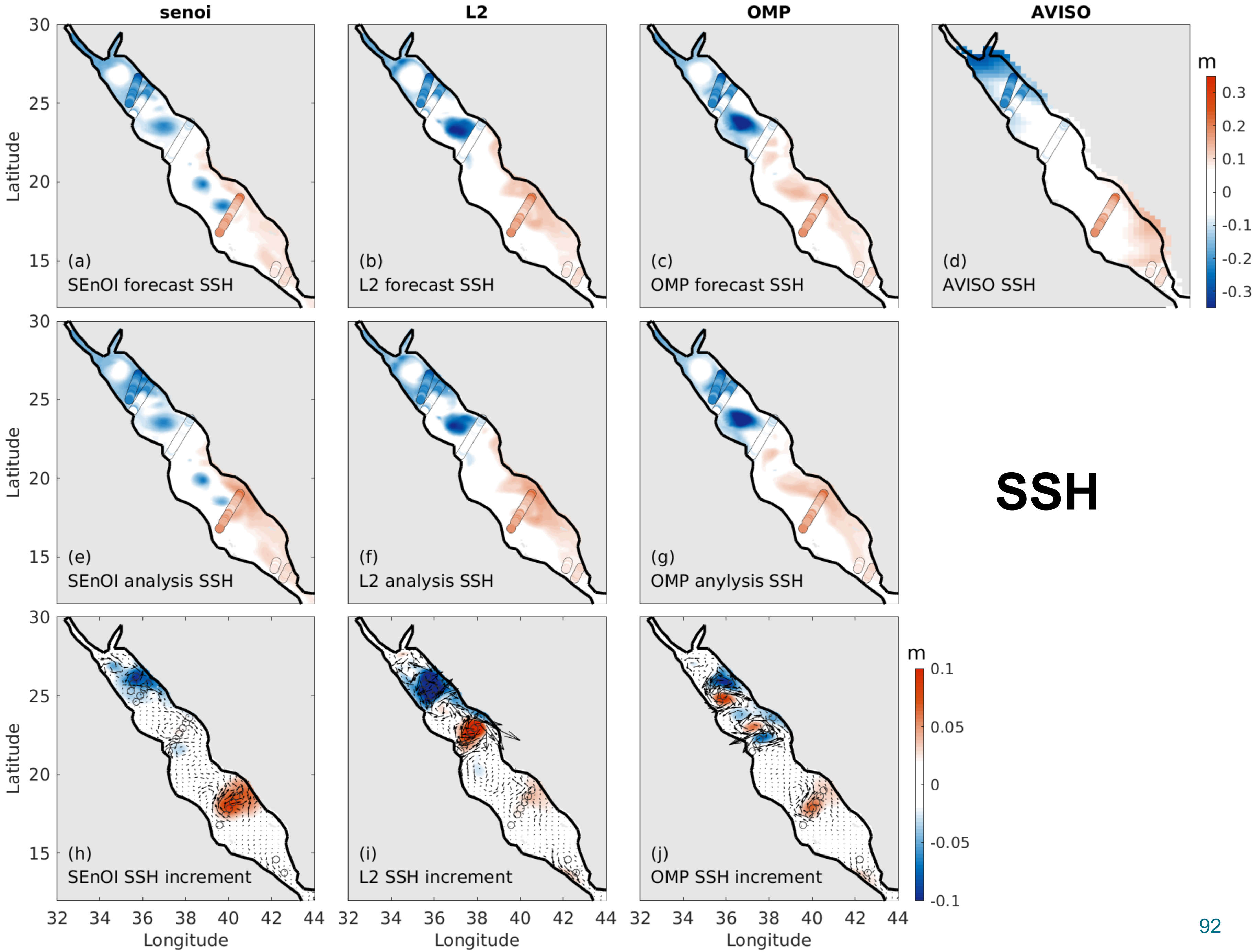
  Keep the most correlated members with the forecast

- Through l1 and l2 norms:

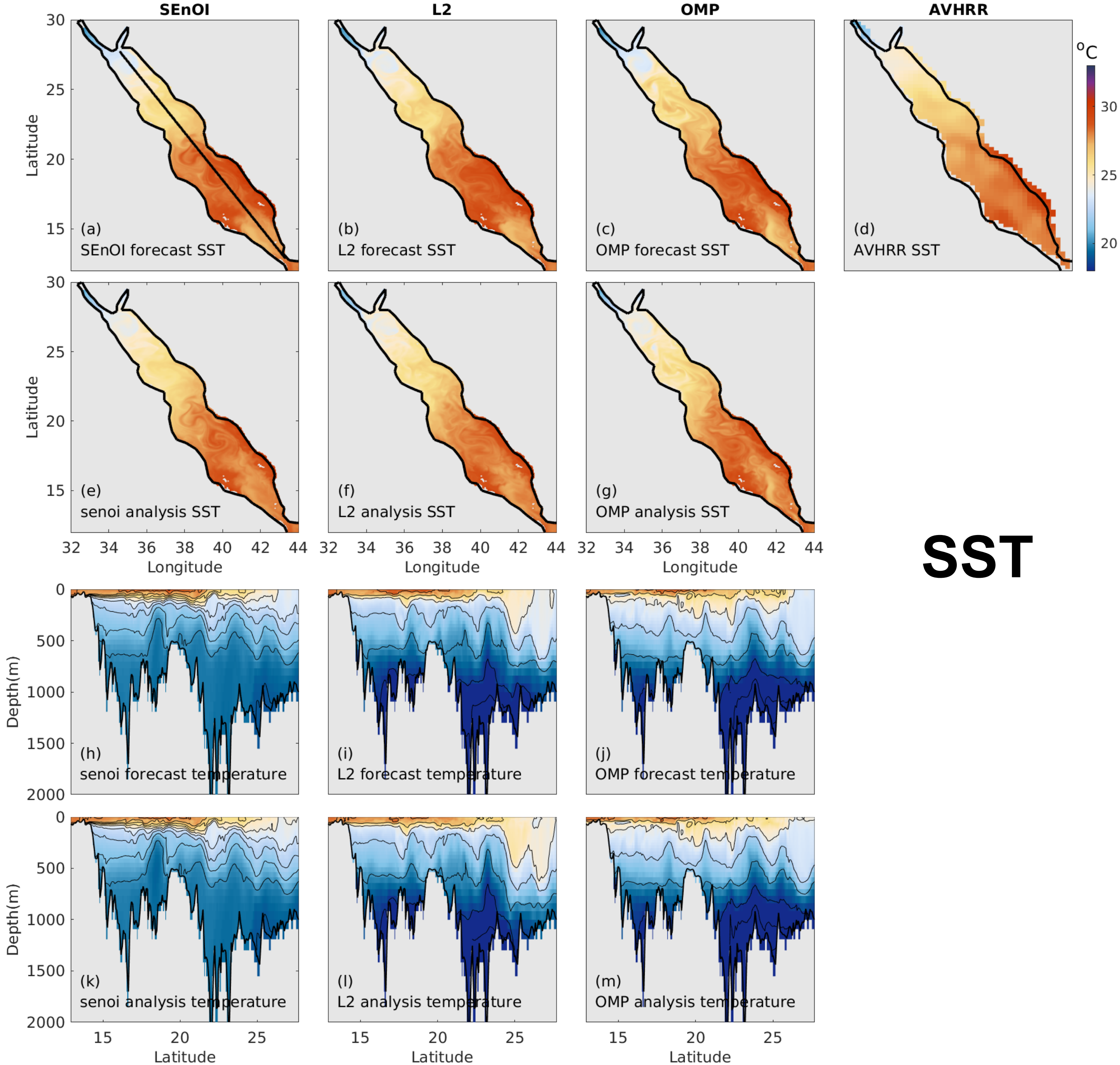
  Keep the dictionary members that are closest to the forecast

- Through orthogonal matching pursuit (OMP):

  Perform a decomposition of the forecast based on the OMP algorithm and keep the members that represent the forecast

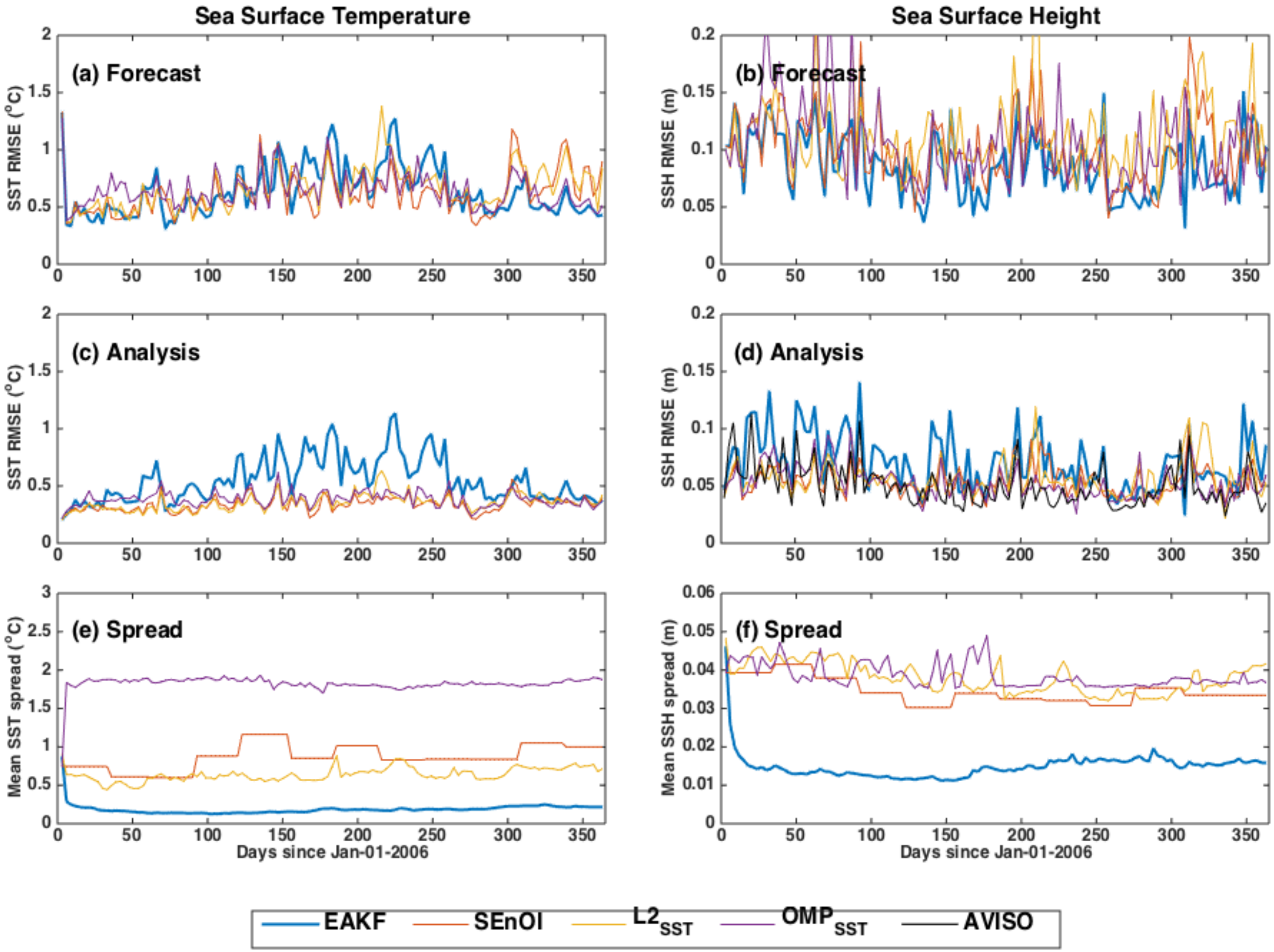

senoi
L2
OMP
AVISO
(a)
SEnOI forecast SSH
(b)
L2 forecast SSH
(c)
OMP forecast SSH
(d)
AVISO SSH
(e)
SEnOI analysis SSH
(f)
L2 analysis SSH
(g)
OMP anylysis SSH
(h)
SEnOI SSH increment
(i)
L2 SSH increment
(j)
OMP SSH increment
Latitude
Longitude
m
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
m
0.1
0.05
0
-0.05
-0.1

SSH

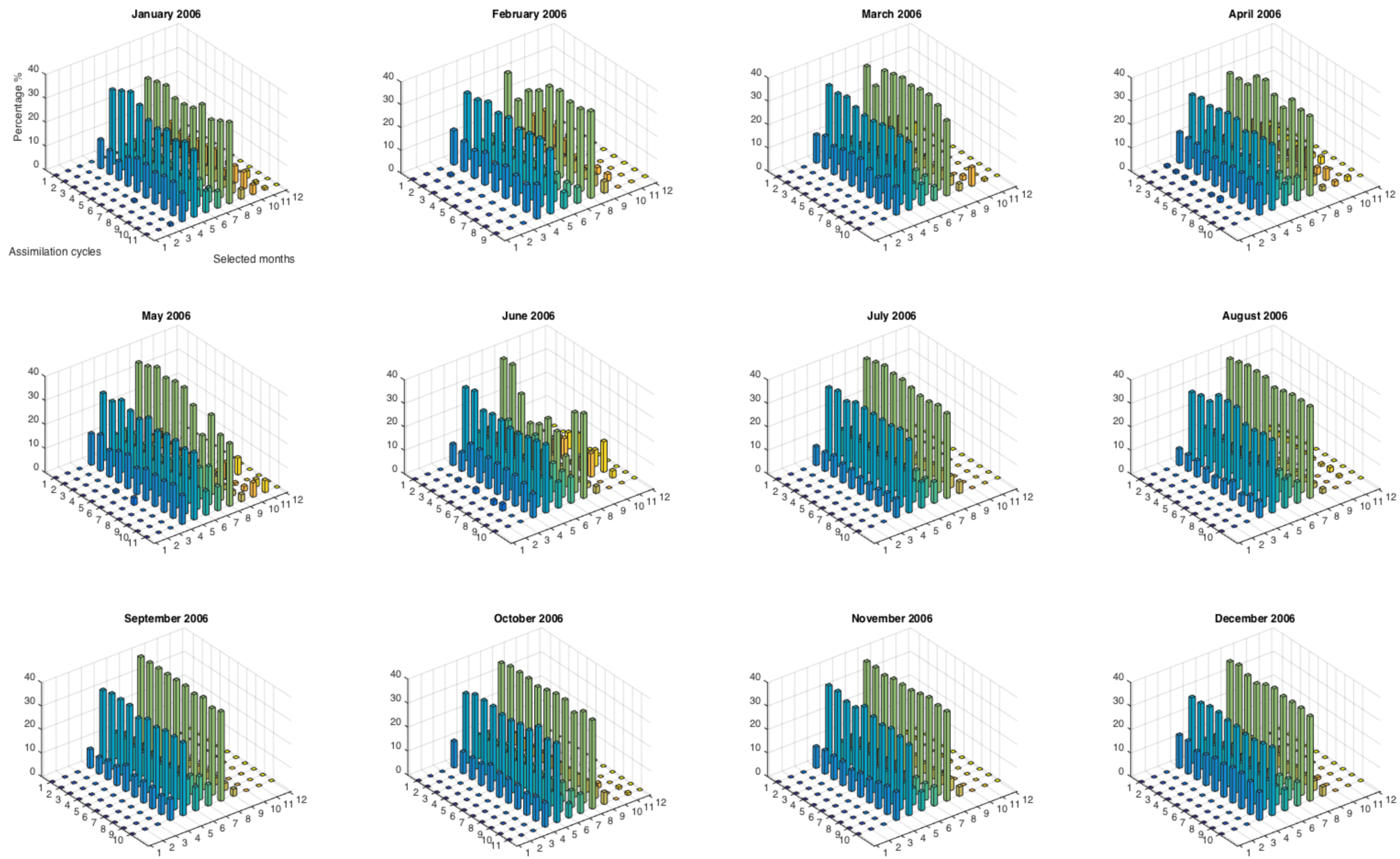

SEnOI
L2
OMP
AVHRR
°C
30
25
20
(a)
SEnOI forecast SST
(b)
L2 forecast SST
(c)
OMP forecast SST
(d)
AVHRR SST
(e)
senoi analysis SST
(f)
L2 analysis SST
(g)
OMP analysis SST
Latitude
Longitude
(h)
senoi forecast temperature
(i)
L2 forecast temperature
(j)
OMP forecast temperature
(k)
senoi analysis temperature
(l)
L2 analysis temperature
(m)
OMP analysis temperature
Depth(m)
Latitude

SST

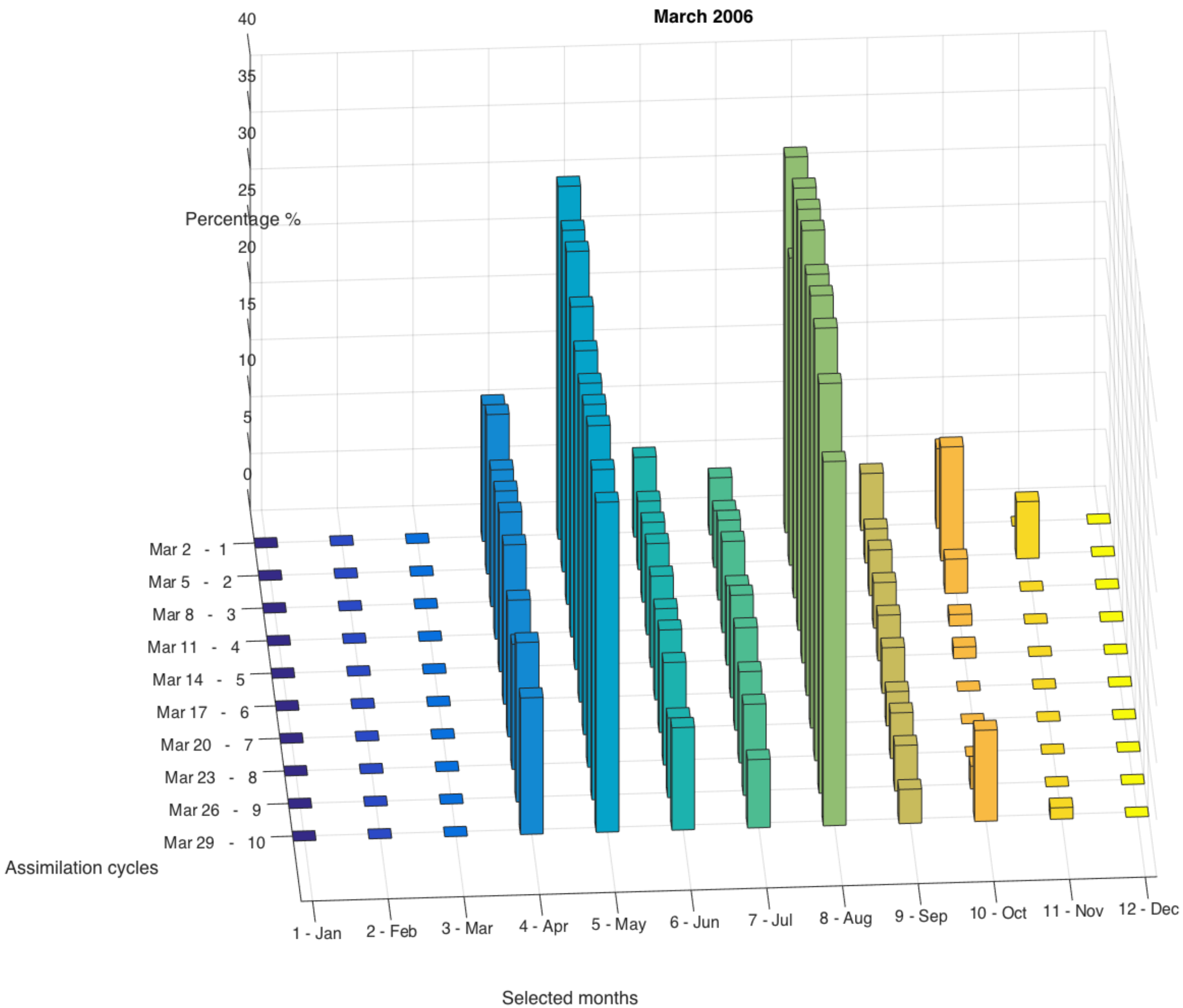
Schemes comparison



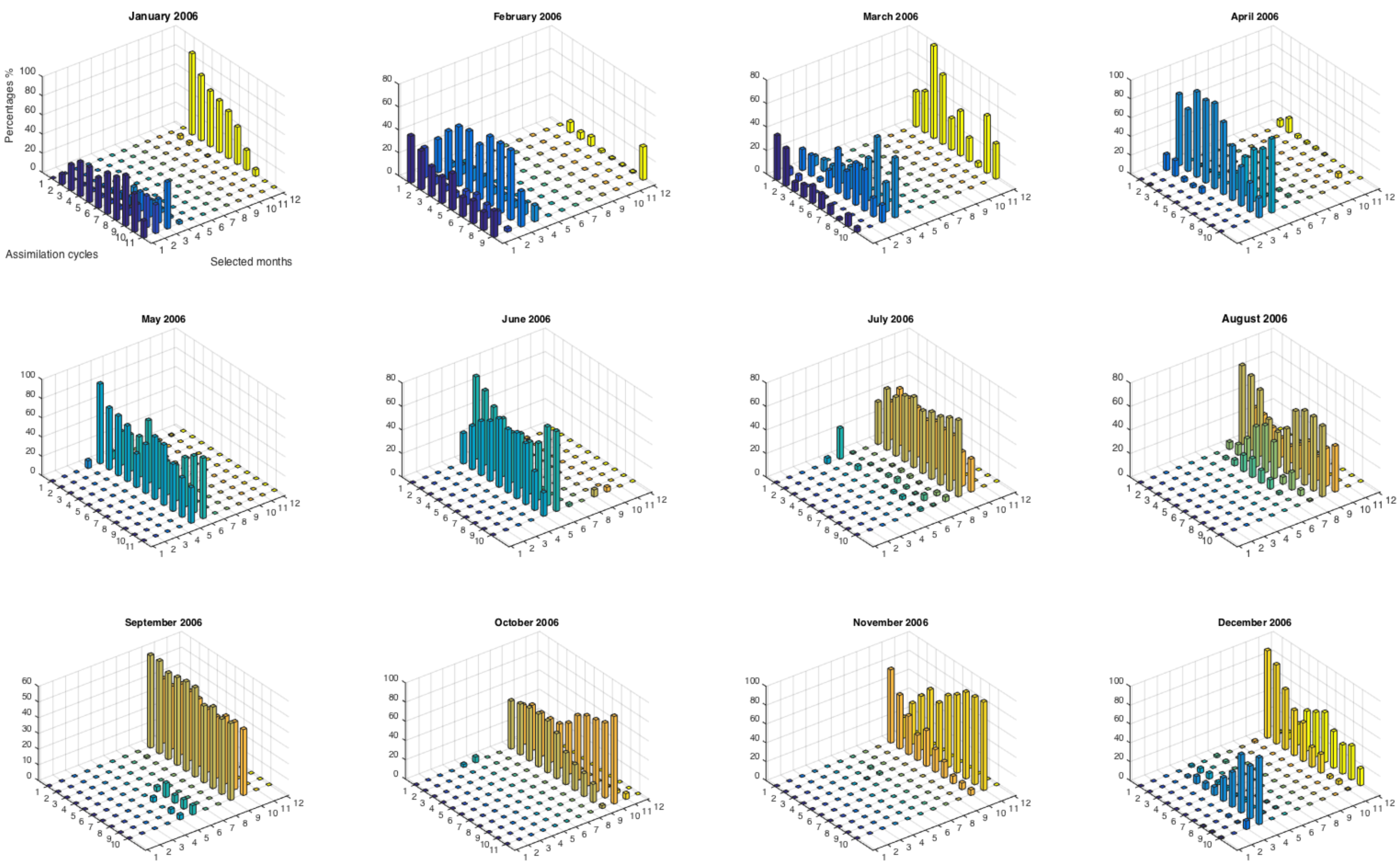
Months of OMP selected members



Months of OMP selected members



Months of l2-norm selected members



Conclusion

- The different OI schemes results are comparable
- The adaptive schemes require more computation
- The Seasonal EnOI seems to be the best choice

Acknowledgment

This research work was supported by King Abdullah University of Science and Technology (KAUST), Saudi Arabia and the Saudi ARAMCO-KAUST Marine Environmental Research Center (SAMERCK). The research made use of the resources of the Super computing Laboratory and computer clusters at KAUST.

King Abdullah University of Science and Technology KAUST

Thank you!