

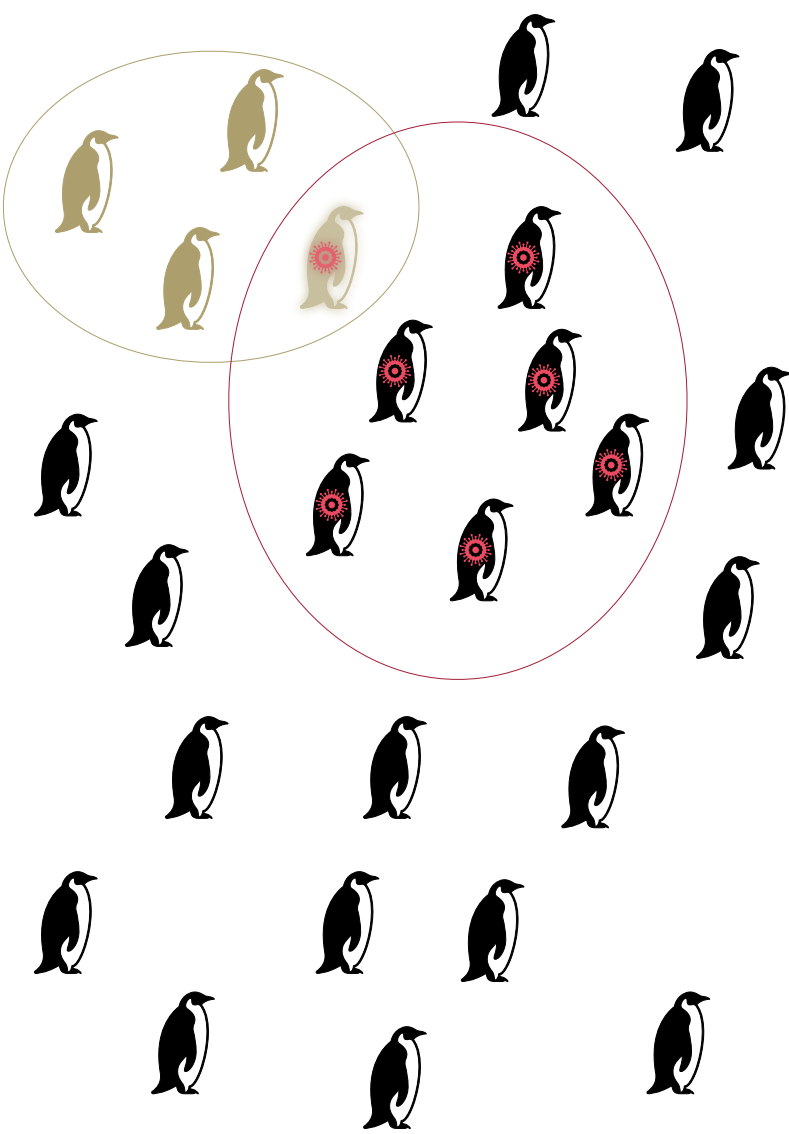
## Modelling by Measurability

What do the following scenarios have in common?

- ▶ Machine learning algorithm with restricted access: privacy preservation, “not-missing-at-random” features, accelerated database access, multi-measurement data [1].
- ▶ Incompatible Quantum physical quantities, e.g. location and impulse [2].
- ▶ Preference ordering gives precise beliefs on events not closed under intersections [3].
- ▶ Frequential probability [4].

(Pre-)Dynkin-System as domain of probability.

## Motivation I

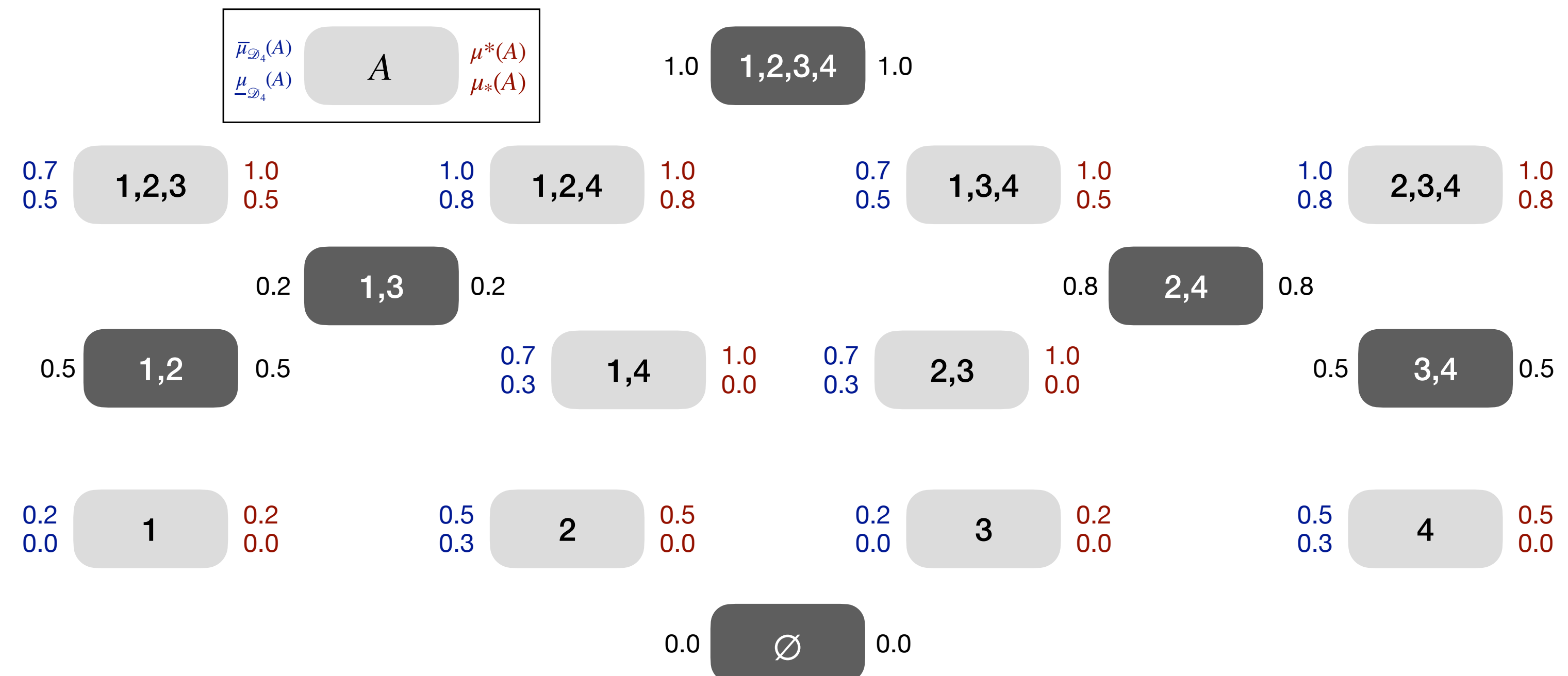


## System of Precision

Imprecise Probability (IP) focuses on imprecision.

We ask: **On which events are imprecise probabilities precise?**

## Motivation II



## Probability on Pre-Dynkin-System

## Definitions

A pre-Dynkin-system  $\mathcal{D} \subseteq 2^\Omega$  on  $\Omega$  fulfills:

- ▶  $\emptyset \in \mathcal{D}$ ,
- ▶  $D \in \mathcal{D}$  implies  $D^c := \Omega \setminus D \in \mathcal{D}$ ,
- ▶  $C, D \in \mathcal{D}$  with  $C \cap D = \emptyset$  implies  $C \cup D \in \mathcal{D}$ .

A function  $\mu: \mathcal{D} \rightarrow [0, 1]$  is a (finitely additive) **probability on  $\mathcal{D}$** , if:

- ▶  $\mu(\emptyset) = 0$  and  $\mu(\Omega) = 1$ .
- ▶ Let  $C, D \in \mathcal{D}$  such that  $C \cap D = \emptyset$ , then  $\mu(C \cup D) = \mu(C) + \mu(D)$ .

## Extendability = Coherence

## Linking together

- ▶ A probability  $\mu: \mathcal{D} \rightarrow [0, 1]$  is **extendable** if there exists a probability  $\mu': 2^\Omega \rightarrow [0, 1]$  such that  $\mu'|_{\mathcal{D}} = \mu$ .
- ▶ A probability on a pre-Dynkin-system is extendable if and only if it is coherent [5,6].
- ▶ There exists an inner and outer measure extension  $(\mu_*, \mu^*)$  for every probability, and a coherent extension  $(\underline{\mu}_{\mathcal{D}}, \overline{\mu}_{\mathcal{D}})$  for every extendable probability.

## The Set Structure of Precision Simple but Insightful

Let  $\mathcal{F}$  be an algebra on  $\Omega$ . Let  $\ell: \mathcal{F} \rightarrow [0, 1]$  and  $u: \mathcal{F} \rightarrow [0, 1]$  be two set functions s.t.:

**Normalization:**  $u(\emptyset) = \ell(\emptyset) = 0$ .

**Conjugacy:**  $u(A) = 1 - \ell(A^c)$  for  $A, A^c \in \mathcal{F}$ .

**Subadditivity of  $u$ :** for  $A, B \in \mathcal{F}$  such that  $A \cap B = \emptyset$  then  $u(A \cup B) \leq u(A) + u(B)$ .

**Superadditivity of  $\ell$ :** for  $A, B \in \mathcal{F}$  such that  $A \cap B = \emptyset$  then  $\ell(A \cup B) \geq \ell(A) + \ell(B)$ .

Then  $u$  and  $\ell$  define a finitely additive probability measure  $\mu := u|_{\mathcal{D}} = \ell|_{\mathcal{D}}$  on a pre-Dynkin-system  $\mathcal{D} \subseteq \mathcal{F}$ .

Coherent imprecise probabilities [5] fulfill all the required properties.

## (Dual) Credal Set Function

## Set System to IP

Let  $\mathcal{F}$  be an algebra on  $\Omega$  and  $P$  all probabilities on  $\mathcal{F}$ . For a fixed finitely additive probability  $\psi \in P$ , we define the **credal set function**,

$$m: 2^{\mathcal{F}} \rightarrow 2^P, m(\mathcal{A}) := \{\nu \in P: \nu(A) = \psi(A), \forall A \in \mathcal{A}\},$$

and the **dual credal set function**,

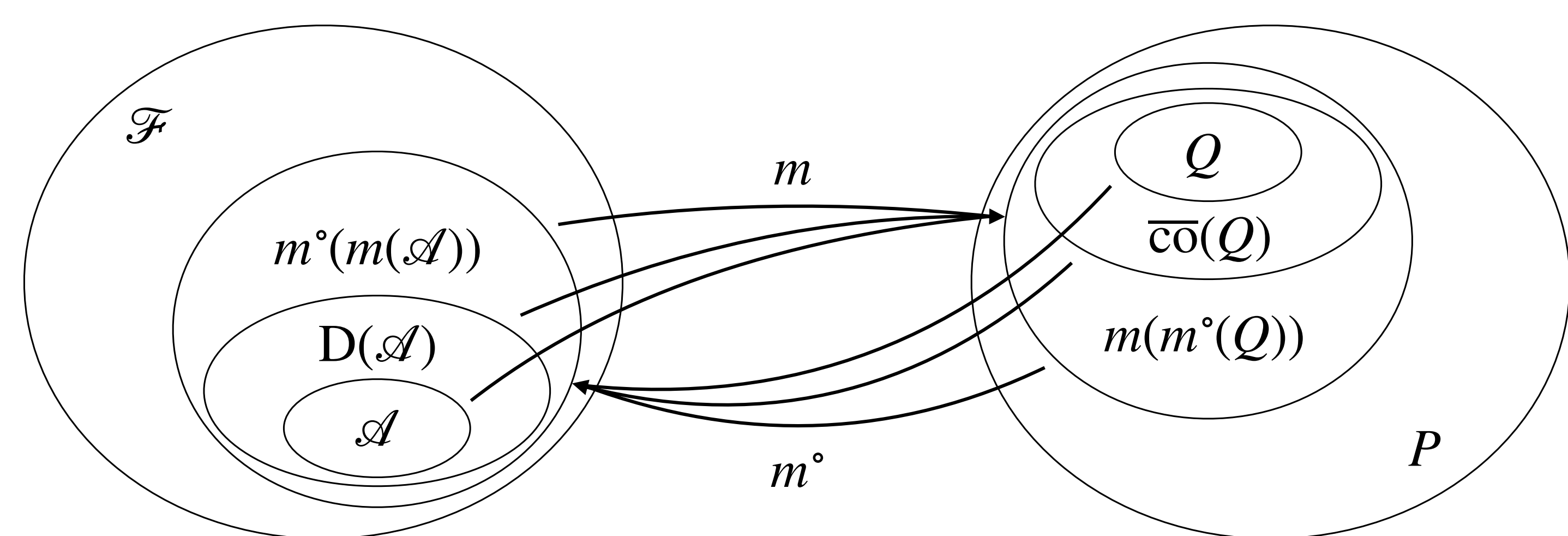
$$m^\circ: 2^P \rightarrow 2^{\mathcal{F}}, m^\circ(Q) := \{A \in \mathcal{F}: \nu(A) = \psi(A), \forall \nu \in Q\}.$$

## Set Systems $\leftrightarrow$ IP

## A Lattice Duality

- ▶ The set  $m(Q)$  is a credal set, i.e. non-empty, weak\*-closed and convex subset of  $P$ .
- ▶ The set  $m^\circ(\mathcal{A})$  is a pre-Dynkin-system.
- ▶ The credal set function  $m$  and the dual credal set function  $m^\circ$  form a so-called Galois connection, i.e.  $\mathcal{A} \subseteq m^\circ(Q) \Leftrightarrow Q \subseteq m(\mathcal{A})$ .

Galois connections induce a lattice duality between so-called bipolar-closed set systems and credal sets.



We denote the pre-Dynkin-hull with  $D$  and the convex closure with  $\overline{\cdot}$ .

## Departing From Here

## Future

- ▶ Generalize from probabilities and set structures to expectation-type functional and systems of gambles.
- ▶ Coherent imprecise probabilities parametrized by pre-Dynkin-systems versus other parametrizations.
- ▶ Social intersectionality and pre-Dynkin-systems.

## The FMLS group

## Foundations of Machine Learning Systems



**Goal:** to develop new and better foundations for machine learning (ML) systems

## References

- [1] E. Eban, E. Mezuman, and A. Globerson. Discrete Chebyshev classifiers. ICML, 2014.
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- [3] L. G. Epstein and J. Zhang. Subjective probabilities on subjectively unambiguous events. Econometrica, 2001.
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