OVERVIEW We will go through a digest of six papers. I have broken abstracts or introductions into numbered points. I have emboldened key terms for ease of reading and I have underlined many technical terms. I will be collecting feedback from the you on Zulip.

## INSTRUCTIONS

- If you haven't already done so, please create a Zulip account using the *link* on the meetup.com meeting page.
- We will discuss readings on the Zulip thread entitled #learning: reading groups / Statistics reading group.
- I will be collecting materials from you on the thread #learning: reading groups / Statistics reading group—'Housekeeping'
- I have numbered every point so that you can quickly note every concept that is important to you.
- For each paper, please write down the **author's name** followed by a list of point numbers that are most interesting you.
- For each paper, please write at least one sentence relating the most compelling points to your own work or interests
- Lastly, please pick the two papers you most want to read right away.
- Please list these two papers in the following fashion:

'Top Papers: (1) AuthorName, (2) AuthorName'

- Submit all this information as a post on the thread #learning: reading groups / Statistics reading group—'Housekeeping'
- Next, I will decide which paper to read based on your feedback.
- Finally, we will **revisit** our chosen paper and **briefly** decide what **sec**tions to read.

Your feedback will help us chart a **roadmap** through the material. We will chat more on Zulip about that, as well as other topics such as contriving exercises for ourselves and writing posts on the Applied Category Theory Wiki.

#### What is a statistical model?

Peter McCullagh

- 1. This paper addresses two closely related questions,
- 2. "What is a statistical model?" and "What is a parameter?"
- 3. The notions that a model must "make sense," and that a parameter must "have a well-defined meaning" are...well understood [in practice, but absent from most formal theories...
- 4. In this paper, these concepts are defined in algebraic terms, using morphisms, functors and natural transformations.
- 5. It is argued that inference on the basis of a model is not possible unless the model admits a natural extension that includes the domain for which inference is required.
- 6. For example, prediction requires that the domain include all future units, subjects or time points.
- 7. Although it is usually not made explicit, every sensible statistical model admits such an extension.
- 8. Examples are given to show why such an extension is necessary and why a formal theory is required.
- 9. In the definition of a subparameter, it is shown that certain parameter functions are natural and others are not.
- 10. Inference is meaningful only for natural parameters.
- 11. This distinction has important consequences for the construction of prior distributions
- 12. and also helps to resolve a controversy concerning the Box-Cox model.

Statistical Isomorphism Norman Morse and Richard Sacksteder

- 1. A statistical *problem* consists in part of a sample space and a set of probability distributions on that space.
- 2. One can speak of the space and the set of probability distributions as a "statistical system."
- 3. ...different statistical systems...may be considered equivalent [if] [stating] a...statistical problem in terms of either system gives the statistician the same amount of...information with respect to the...problem.
- 4. This notion of equivalence has been given precise development in a number of papers dealing with the concept of **sufficiency** and with the "comparison of experiments," as will be noted below.
- 5. .[It is] generally accepted that...Given a sample space and a [set of parameterized probability distributions] on the space,
- 6. if there is a map [giving] each point of [one] sample space something like a probability distribution on a second space,
- 7. and [there is] an induced set of probability distributions on the second space corresponding to those given on the first,
- 8. then...the second space and the induced probability distributions [are] second or induced statistical system,
- 9. and...the first system [is] sufficient for the second. Two systems are "equivalent" if each is sufficient for the other.
- 10. ...The formal definition of statistical isomorphism which we give is not convenient for determining whether two statistical systems are isomorphic...
- 11. .[We need a] complete set of invariants of the isomorphism classes. Our main result, Theorem 2, provides such a set of invariants for dominated statistical systems.
- 12. The invariants have a simple intuitive interpretation which we illustrate in a simple case in this section.

# Probability Sheaves and the Giry Monad

Alex Simpson

- 1. I introduce the notion of probability sheaf,
- 2. which is a mathematical structure capturing the relationship between probabilistic concepts (such as random variable) and sample spaces.
- 3. Various probability-theoretic notions can be (re)formulated in terms of category-theoretic structure on the category of probability sheaves.
- 4. As a main example, I consider the Giry monad, which, in its original formulation, constructs spaces of probability measures.
- 5. I show that the Giry monad generalises to the category of probability sheaves, where it turns out to have a simple, purely category-theoretic definition.

The Algebra and Machine Representation of Statistical Models Evan Patterson

- 1. This dissertation takes steps toward digitizing and systematizing... statistical models and data analyses.
- 2. Using tools from...categorical logic, a precise analogy is drawn between [statistical models] and [logical models]...
- 3. Statistical theories, being algebraic structures, are amenable to machine representation and are equipped with morphisms that formalize the relations between different statistical methods.
- 4. ...a software system for creating machine representations of data analyses, in...Python or R programs, is designed and implemented.
- 5. The representations aim to capture the *semantics of data analyses*, independent of the programming language and libraries in which they are implemented.
- 6. ...The necessary background in category theory is presented in Chapter 2.
- 7. ...In Chapters 3 and 4, I develop the algebra of statistical theories, [models], and their morphisms.
- 8. ...In the second major part, I describe the design and implementation of a software system for creating semantic representations of data science workflows.
- 9. Chapter 5 [is] on the analysis of data science code...
- 10. In Chapter 6, I present the Data Science Ontology and a procedure for the semantic enrichment of idealized computer programs.
- 11. The concluding Chapter 7 describes limitations of the work, suggests directions for future work, and offers a general outlook on how the structuralist approach to data analysis might transform the scientific process.

# Categorical Probability and Stochastic Dominance in Metric Spaces Paolo Perrone

Disclaimer: There is a lot of overlap between this thesis and papers coauthored by Perrone and Fritz. We can select readings from this dissertation, or corresponding papers, depending on interest and other factors. Think of this outline as a multi-source summary.

- 1. In this work we introduce...category-theoretical concepts...to study probability distributions on metric spaces and ordered metric spaces.
- 2. The leading themes in this work are Kantorovich duality [Vil09, Chapter 5],
- 3. Choquet theory [Win85, Chapter 1],
- 4. and the categorical theory of monads and their algebras [Mac00, Chapter VI].
- 5. ...Probability monads[, discussed in Chapter 1,] can be interpreted as a categorical tool to talk about random elements of a space [and their convex combinations].
- 6. ...to every monad corresponds an adjunction.
- 7. For probability monads, this adjunction can be interpreted in terms of Choquet theory.
- 8. In Chapter 2 we define a probability monad on the category of complete metric spaces and 1-Lipschitz maps called the **Kantorovich monad**...
- 9. This monad assigns to each complete metric space X its Wasserstein space PX, which is itself a complete metric space.
- 10. In Chapter 3 we extend the Kantorovich monad of Chapter 2 to metric spaces equipped with a partial order. The order is inherited by the Wasserstein space, and is called the stochastic order.
- 11. ...we define a compatibility condition of the order with the metric...We call the spaces with this property L-ordered spaces
- 12. ...In Chapter 4 we study a different order between probability measures, which [points] in the direction of **increasing randomness**.
- 13. ...we develop a new categorical formalism to describe operations evaluated partially.
- 14. ...the partial evaluation order is equivalent to the order known in the literature as the convex [order] or Choquet order.
- 15. ...we study the relation between these partial evaluation orders and convex functions
- 16. ...[we] derive a [new] general duality result valid on all ordered Banach spaces
- 17. ...for every two probability measures p and q over A,  $\int f dp \leq \int f dq$  for all convex monotone functions f if and only if  $p \leq_l q$  for the lax partial evaluation order.

## A synthetic approach to Markov kernels, conditional independence and theorems on sufficient statistics Tobias Fritz

- 1. We develop Markov categories as a framework for synthetic probability and statistics...
- 2. ...we treat the following concepts in purely abstract categorical terms:
- 3. conditioning and disintegration;
- 4. various versions of conditional independence and its standard properties;
- 5. conditional products;
- 6. almost surely;
- 7. sufficient statistics;
- 8. versions of theorems on sufficient statistics due to Fisher-Neyman, Basu, and Bahadur.
- 9. ...[This approach] provides a uniform treatment of...
- 10. discrete probability theory,
- 11. measure-theoretic probability with general measurable spaces,
- 12. Gaussian probability,
- 13. Markov processes of either of these kinds, and many others.