Uncovering latent jet substructure

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Based on: **hep-ph/1904.04200**
BMD, Darius A. Faroughy, Jernej F. Kamenik
+ Manuel Szewc

BOOST2019, Boston, 23rd July 2019

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Overview

Goal: - unsupervised new physics searches in jets
- train on mixed, unlabelled, imbalanced samples
- sensitivity to small S/B (~1%)
- extract descriptions of signal and background
- interpret 'what the machine has learned'
- no control/side-band regions

Approach: - inspired by Natural Language Processing (NLP)
- generative 'topic' model for jet formation
- extract topics from jet substructure
- use topics for classification
- … all based on Latent Dirichlet Allocation

Related work:
On the topic of jets - Metodiev, Thaler
Operational definition of quark and gluon jets - Komiske, Metodiev, Thaler
CWoLa - Metodiev, Nachman, Thaler
LLP - Dery, Nachman, Rubbo, Schwartzman
CWoLa bump hunt - Collins, Howe, Nachman
(binary)JUNIPR - Andreassen, Feige, Frye, Schwartz

Latent Dirichlet Allocation

Blei, Ng, Jordan
Journal of Machine Learning Research
(2003)

LDA is used for text classification, it is based on a generative model for text documents.

Vocabulary:
list of all words in all documents

Topics:
probability distribution over this vocabulary

Document:
an un-ordered list of words, sampled from the topics

Latent structure:
The topic distributions, and the prior on topic proportions

Latent Dirichlet Allocation

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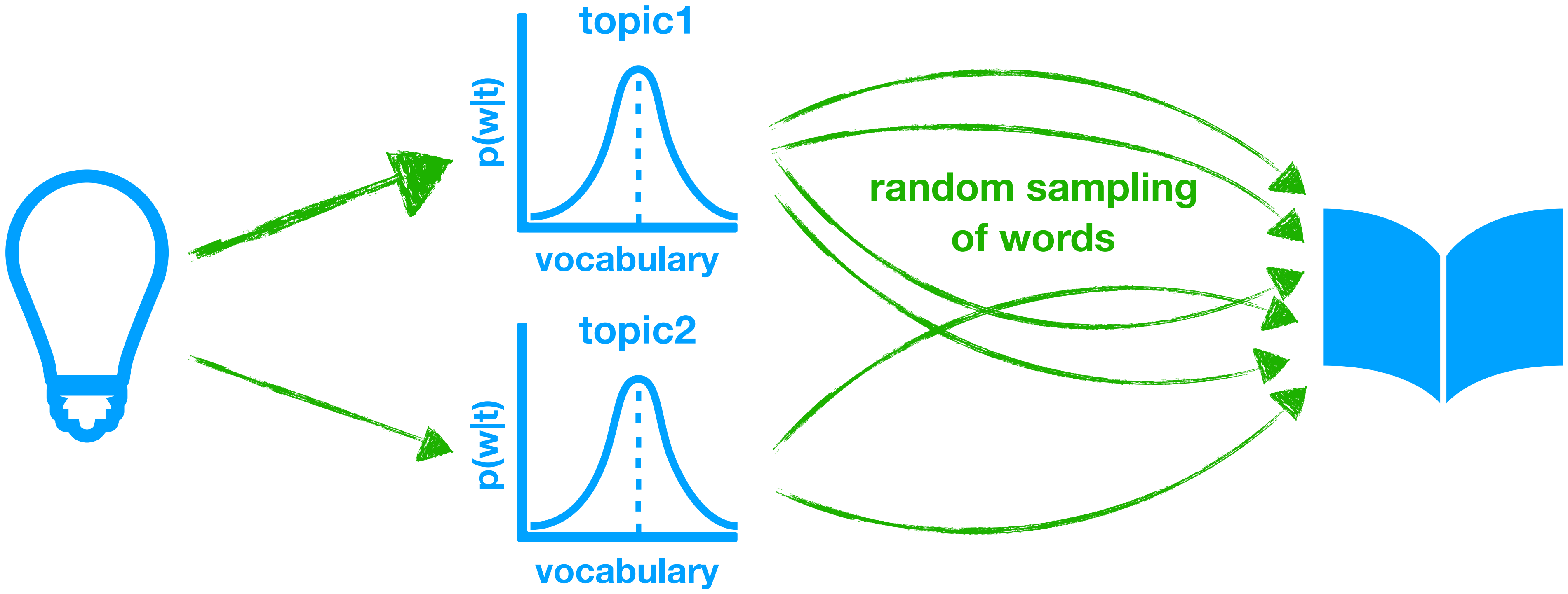

A document is a mixture of topics - no hard assignment
Bag-of-words approximation - no semantic structure is modelled

Latent Dirichlet Allocation

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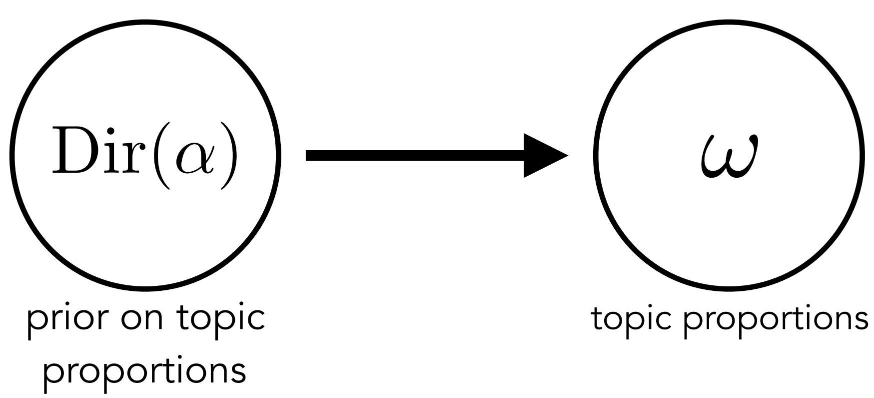
A generative model for a document with K topics



Step 1: sample proportions for each topic, a K-dimensional multinomial ω

Latent Dirichlet Allocation

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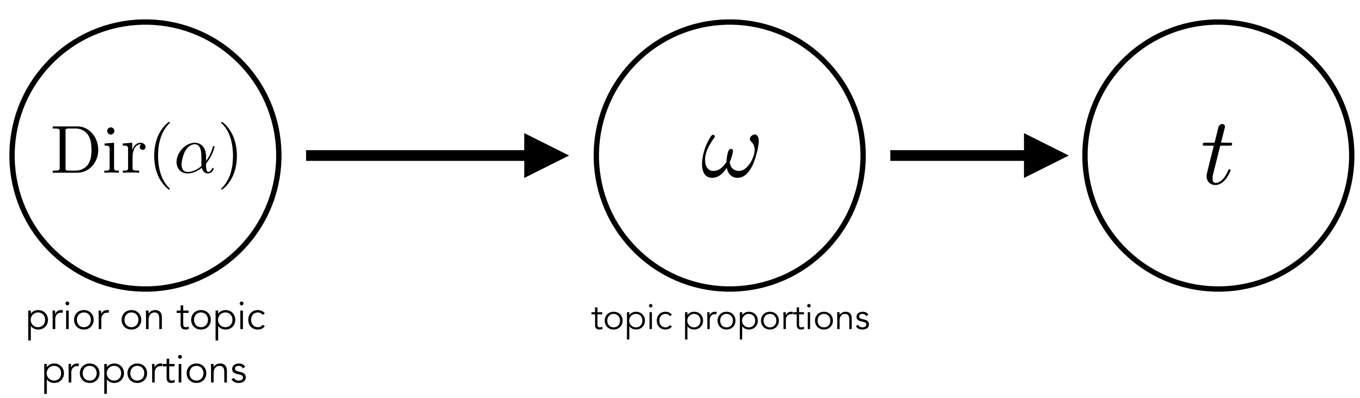

Step 2: sample a single topic from the multinomial

Latent Dirichlet Allocation

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Journal of Machine Learning Research
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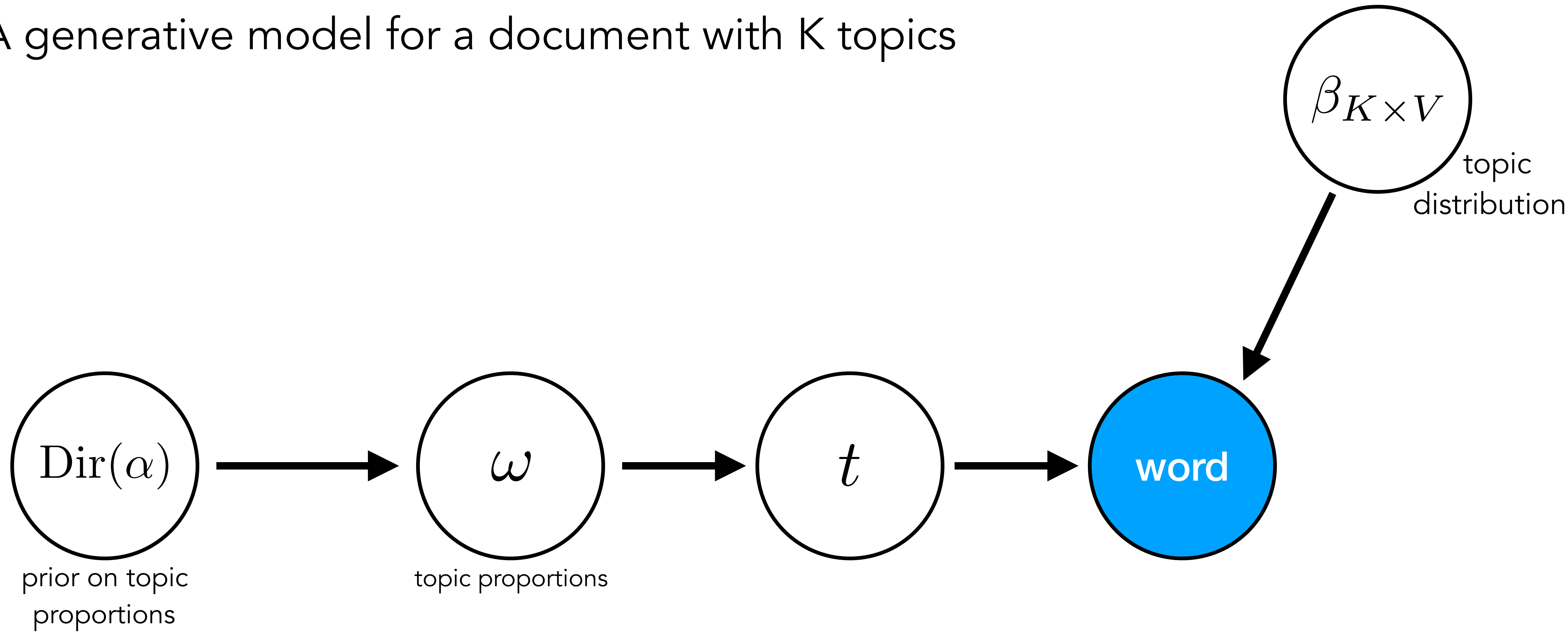

Step 3: sample a word from the appropriate topic distribution

Latent Dirichlet Allocation

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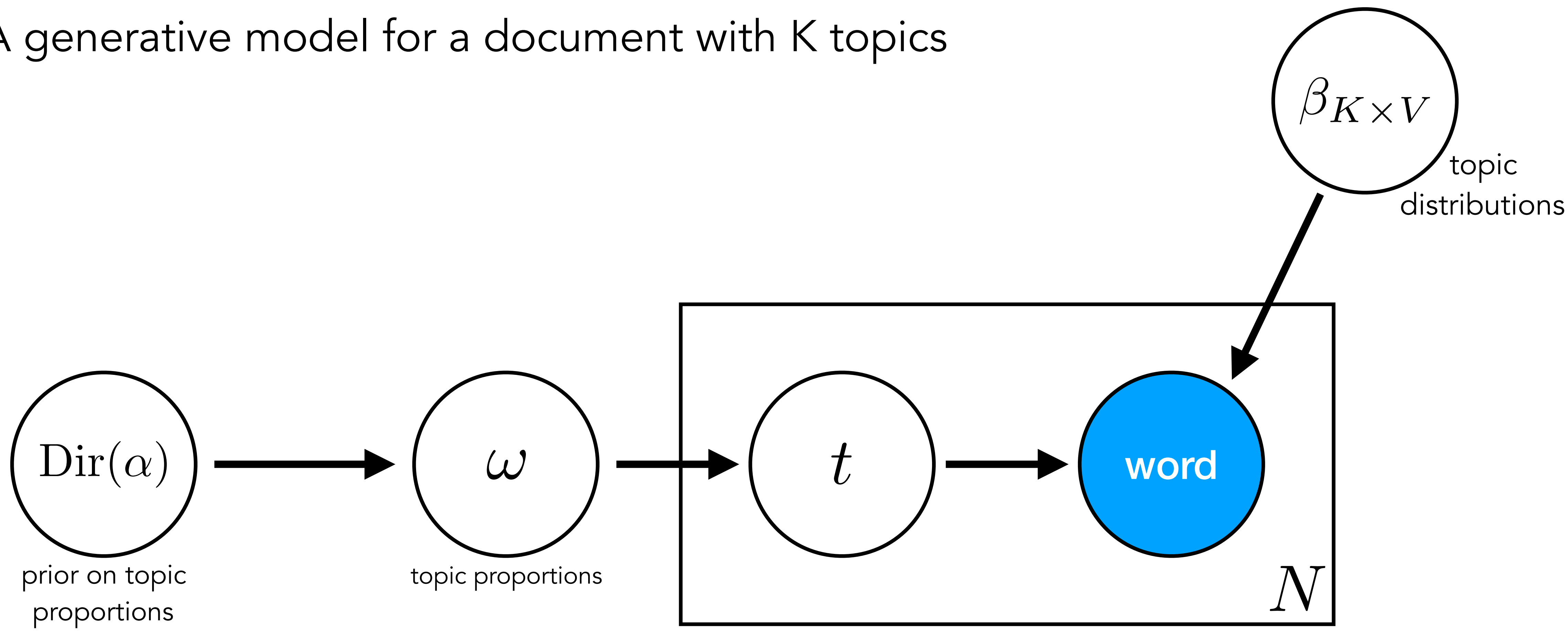
Journal of Machine Learning Research
(2003)

A generative model for a document with K topics

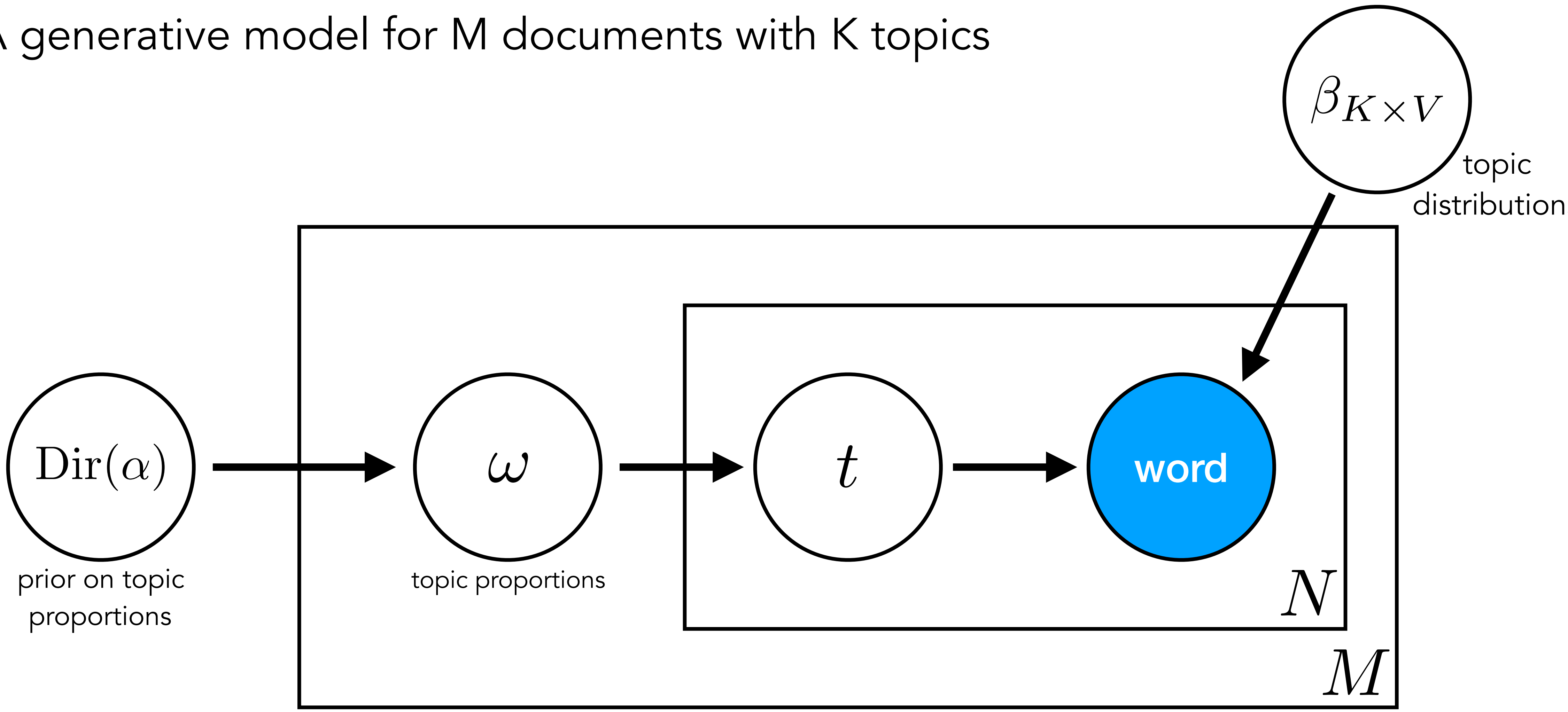


- repeat this for each of the N words in the document

Latent Dirichlet Allocation

Blei, Ng, Jordan
Journal of Machine Learning Research
(2003)

A generative model for M documents with K topics



- repeat again for each of the M documents you want to generate

Latent Dirichlet Allocation

The jet physics edition

LDA is used for text classification, it is based on a generative model for text documents.

~~**Vocabulary:**~~ **substructure features**
list of all words in all documents

~~**Topics:**~~ **underlaying physics**
probability distribution over this vocabulary

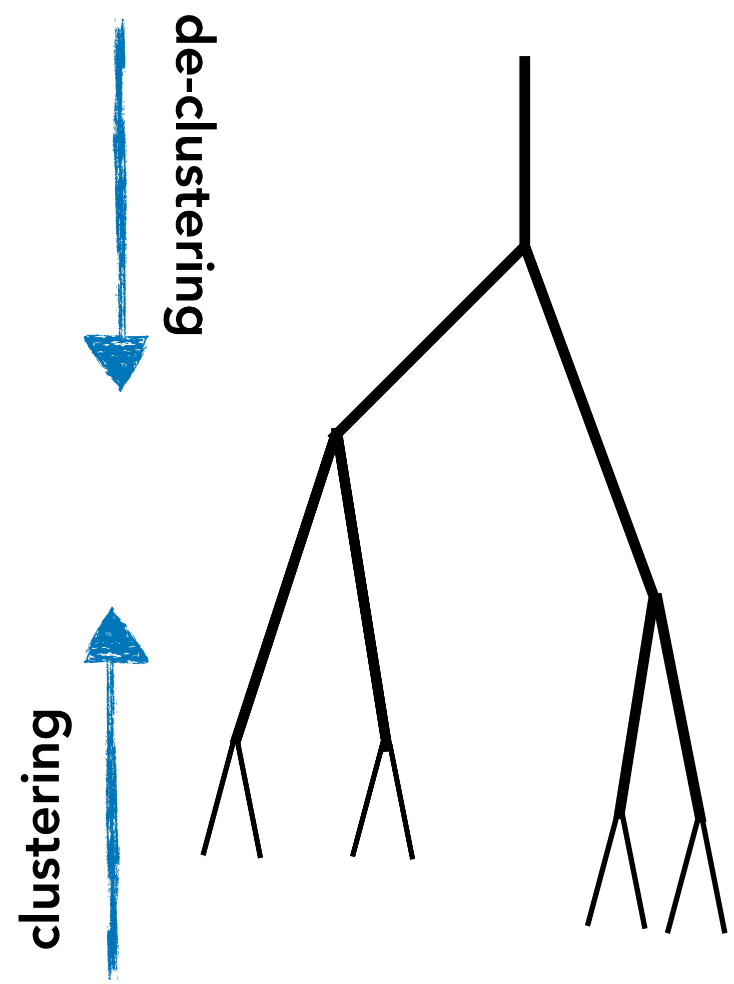
~~**Document:**~~ **a jet or an event**
an un-ordered list of words, sampled from the topics

~~**Latent structure:**~~ **physics underlaying the jets**
The topic distributions, and the prior on topic proportions

Substructure features

We use clustering history of a jet as a proxy for how its substructure was formed

The ‘features’ should encapsulate this tree-structure



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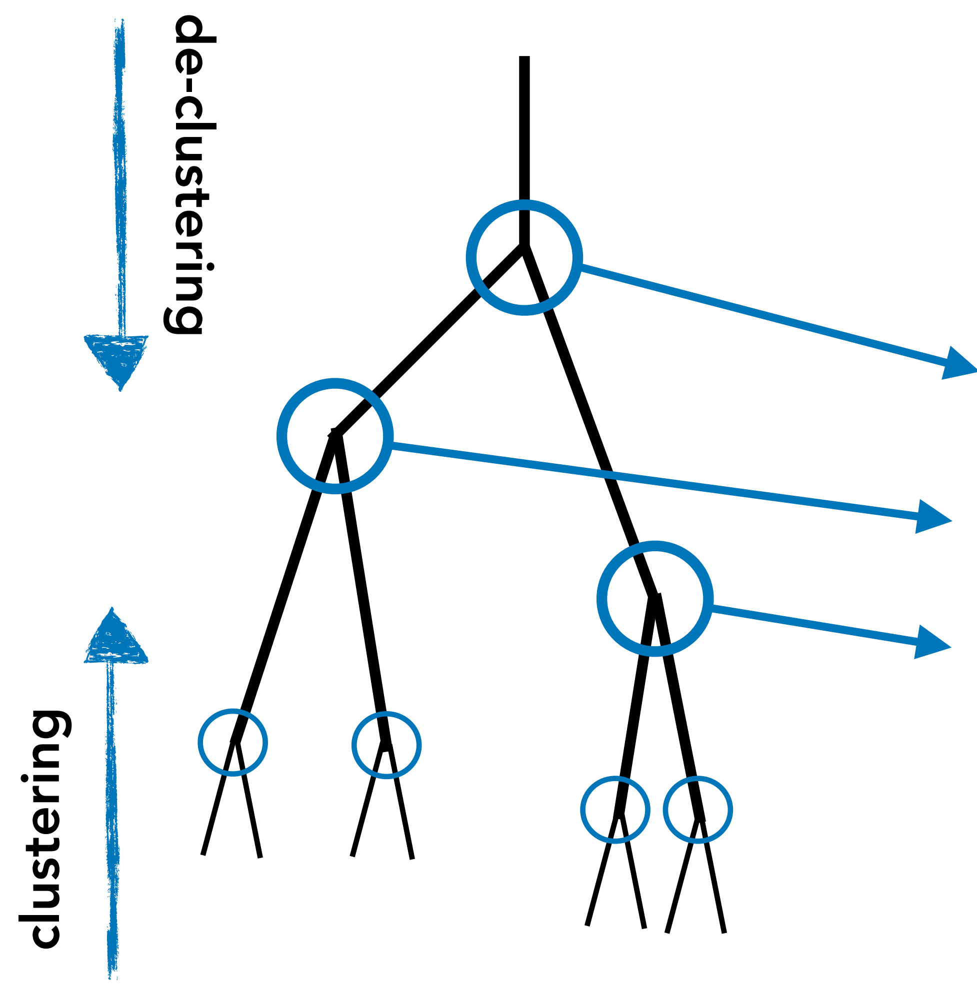

$$\text{feature1} = \left[m_{\text{child}}, \frac{m_{\text{parent1}}}{m_{\text{child}}}, \frac{m_{\text{parent2}}}{m_{\text{parent1}}}, \Delta R_{\text{parents}} \right]$$

$$\text{feature2}$$

$$\ldots$$

$$\boxed{\text{jet} = \{\text{feature1}, \text{feature2}, \text{feature3}, \ldots\}}$$

Extracting the topics

The goal is, given a sample of data, to extract the underlaying topics.

The generative model gives us

$$p(\text{jet}|\alpha, \beta) = \int_\omega p(\omega|\alpha) \prod_{f \in \text{jet}} \left(\sum_t p(t|\omega) p(f|t, \beta) \right)$$

Given a sample of jets, we want to find the set of topics that maximise the log likelihood that the jets were sampled

$$\beta^{\text{MLE}}_{K \times V} = \underset{\beta}{\text{argmax}} \;\; \log \left(\prod_{i=1}^{M} P(\text{jet}_i|\alpha, \beta) \right)$$

- we used the gensim software (it implements a variational EM algorithm)

Radim Rehurek, Petr Sojka, 2010

Topics for new physics

W' example: $pp \to W' \to \phi W \to WWW$ $\quad S/B = 0.011$

J. H. Collins, K. Howe, B. Nachman (2019)

$m_{W'} = 3\ \text{TeV},\ m_\phi = 400\ \text{GeV}$ $\quad m_{jj} \in 2730 - 3190\ \text{GeV}$

Training:

- ~80,000 events
- 2 topics
- mixed, unlabelled sample of QCD and W' events, S/B=0.011
- Dirichlet parameters: $\alpha_1 = 0.99, \quad \alpha_2 = 0.01$

What we want:

- extraction of 2 topics related to signal and background
- use topics for classification/clustering

Topics for new physics

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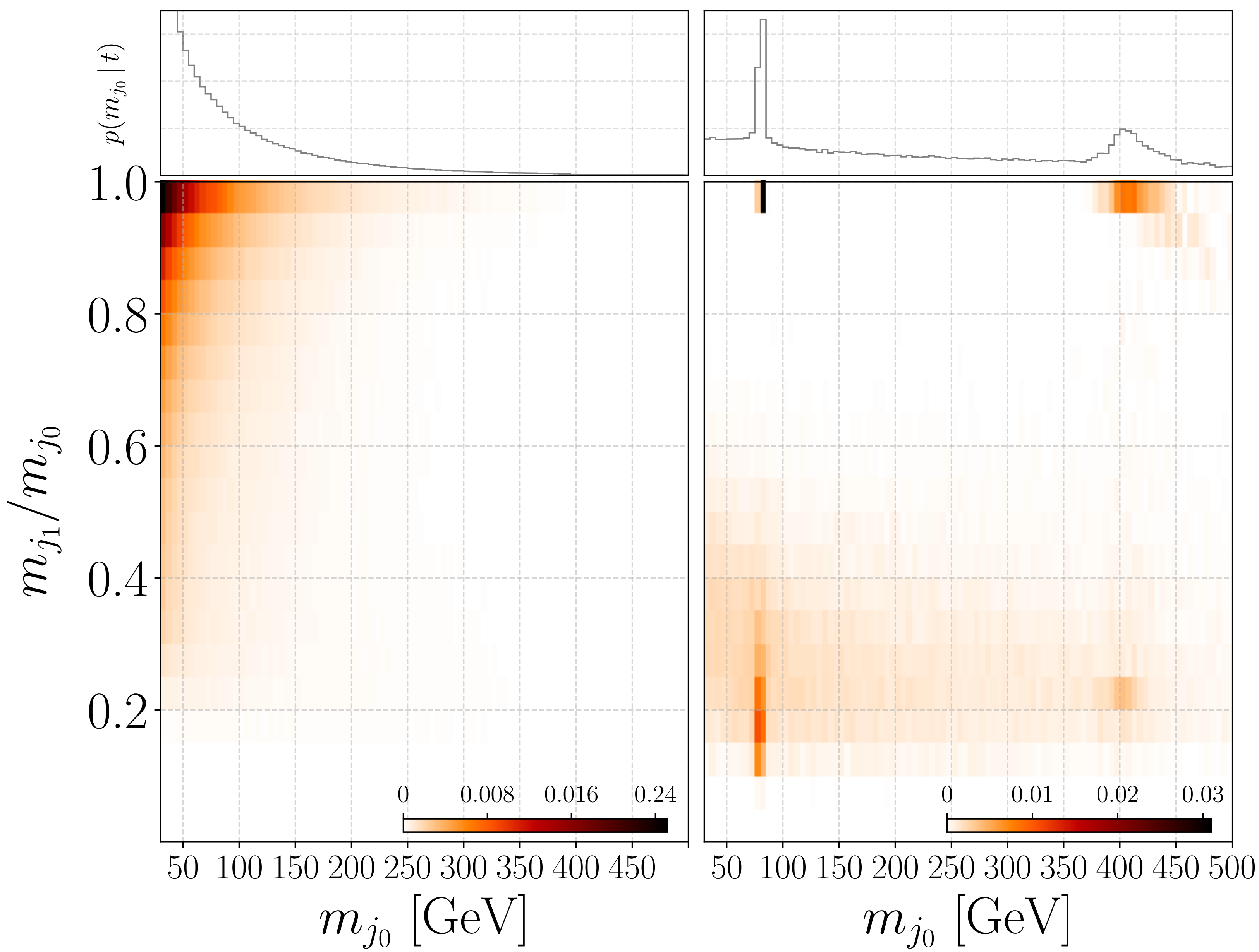

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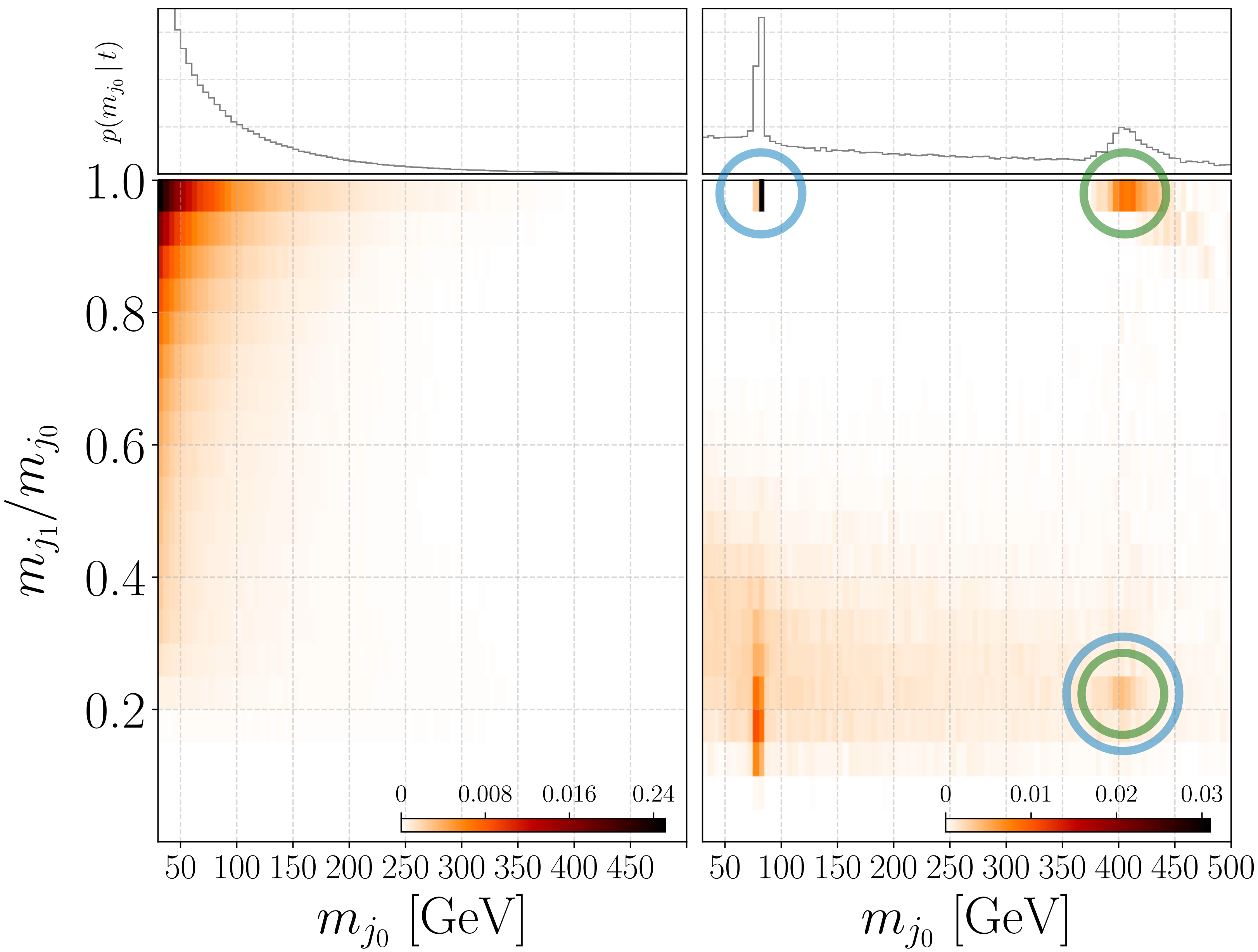

Classification of new physics

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Two methods for classification:

1 - classify using topic proportions inferred in each event

maximise the likelihood for each event to extract ω_1

2 - classify using a likelihood ratio built from the extracted topics

$$\frac{p(\text{event}|\phi_2)}{p(\text{event}|\phi_1)} \leq \text{threshold}$$

Classification of new physics

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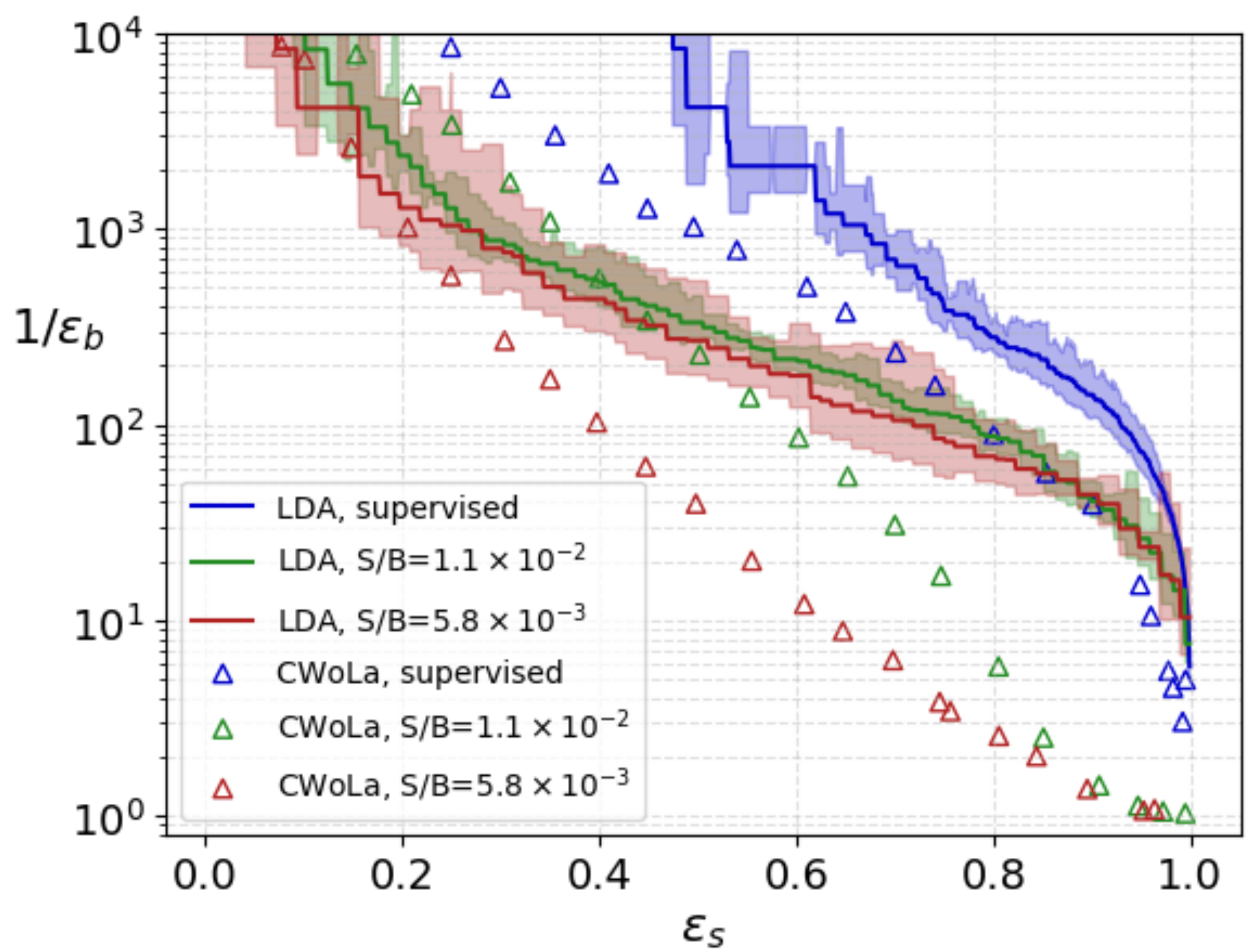

errors estimated using k-folding, with k=10

Uncovering the new physics

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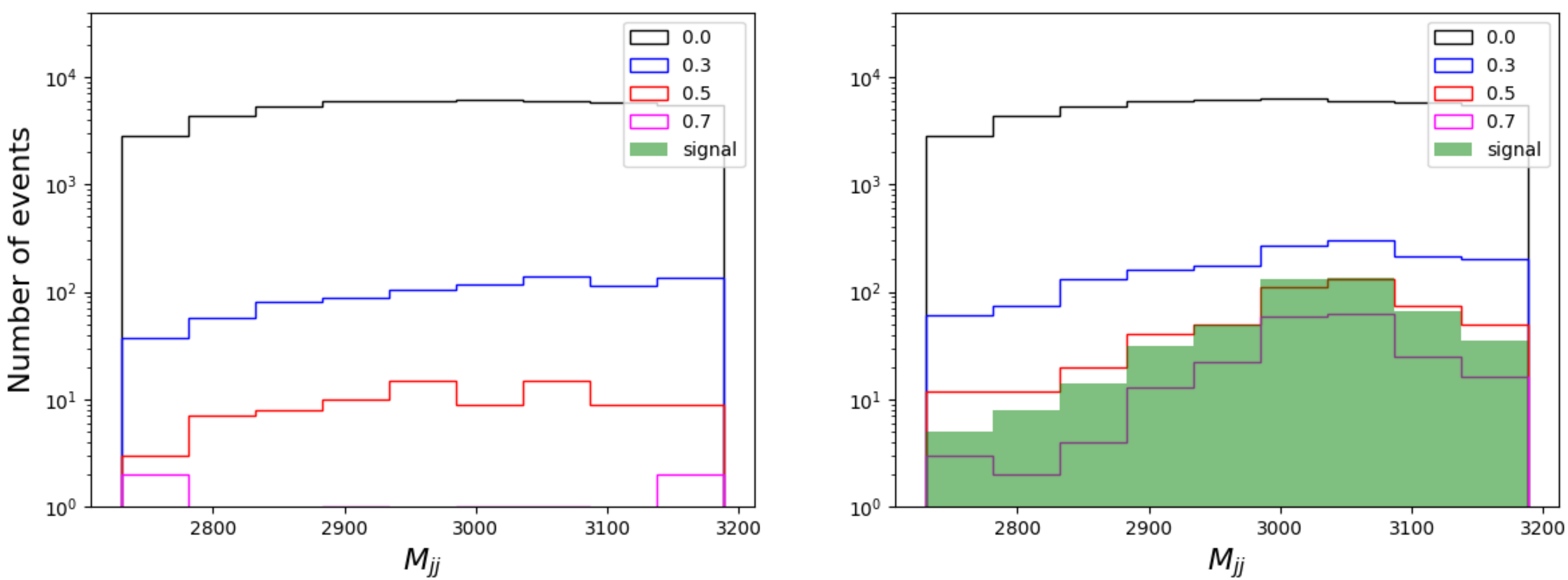


LDA with no signal vs LDA with signal

Summary

Latent Dirichlet Allocation allows us to attack several interesting problems:

- ✓ train on mixed, unlabelled, imbalanced samples
- ✓ sensitivity to small S/B (~1%)
- ✓ extract descriptions of signal and background
- ✓ interpret 'what the machine has learned'
- ✓ no control/side-band regions

So far, this is a proof-of-concept.

Next steps:

- build a specialised topic model for jets/events
- explore classifiers with more than two topics
- hierarchical topic models: number of topics is learned from data
- can this be optimised with deep learning?
- better understand the relationship between the topics and the physics
- more applications: SM, more BSM, pile-up mitigation, …

additional slides

The Dirichlet prior

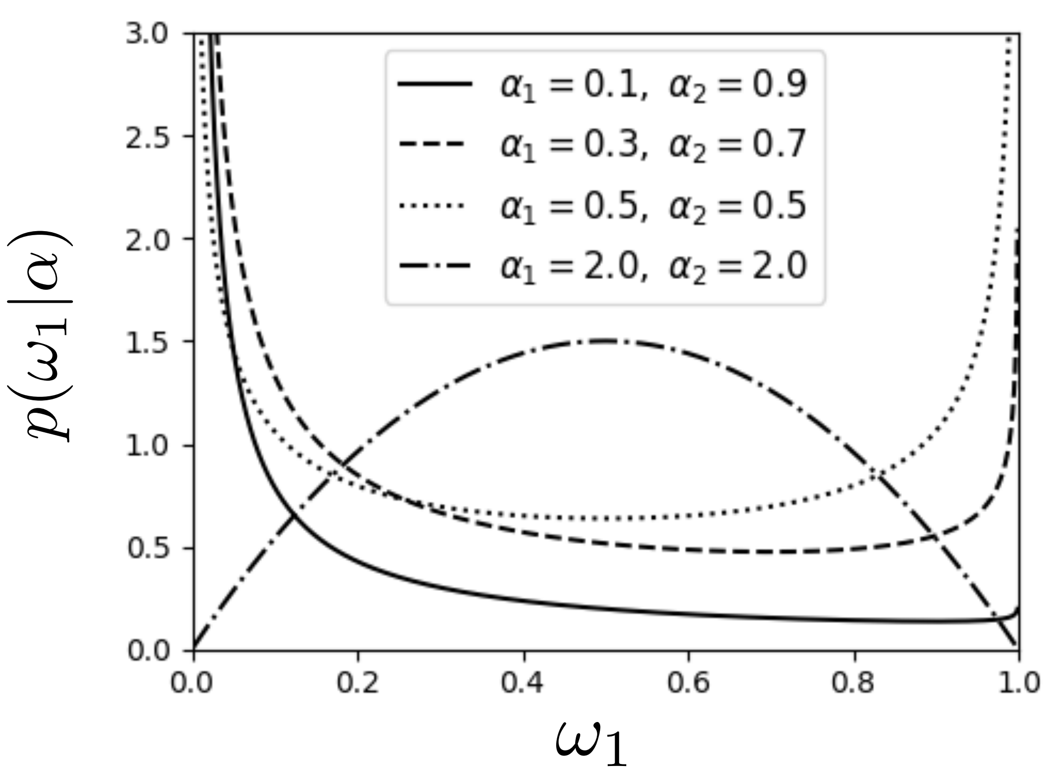
This determines the prevalence of the topics both in the whole sample, and per jet/event

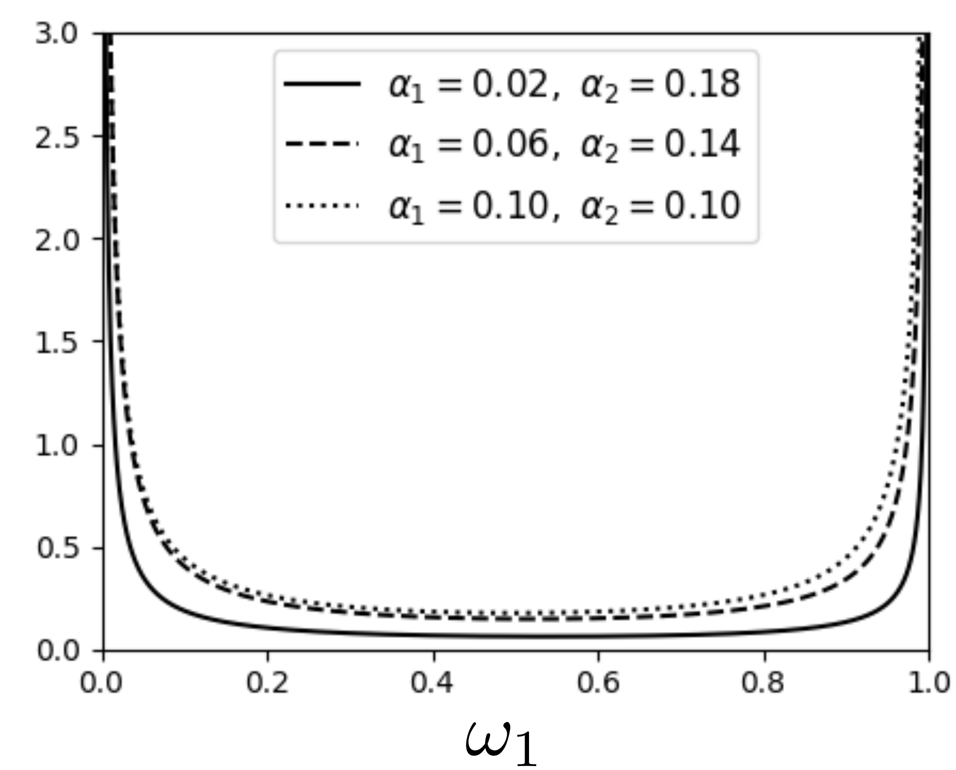
- crucial for sensitivity to small S/B

Basic scenario: **two topics** - one signal, one background

Dirichlet distribution → beta distribution

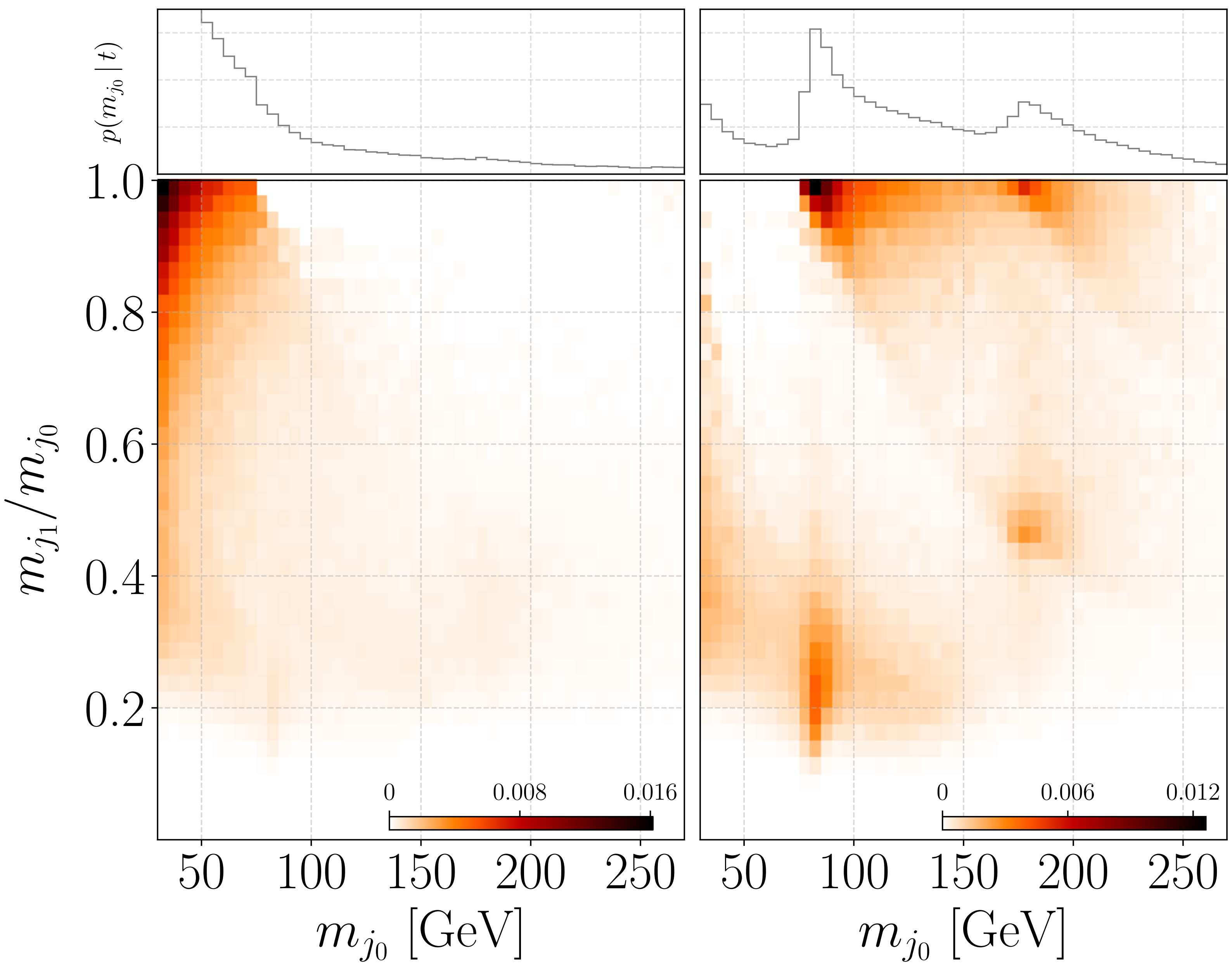
$$\mathrm{B}(\omega_1;\alpha_1,\alpha_2) = \frac{\Gamma(\alpha_1)\Gamma(\alpha_2)}{\Gamma(\alpha_1+\alpha_2)}\omega_1^{\alpha_1-1}(1-\omega_1)^{\alpha_2-1} \qquad \frac{\alpha_2}{\alpha_1} = \frac{\omega_2}{\omega_1}\bigg|_{\mathrm{sample}}$$





Topics for tops

$$pp \to t\bar{t} \to W^+W^-b\bar{b}, \quad S/B = 1, \quad \alpha_1 = \alpha_2 = 0.5$$



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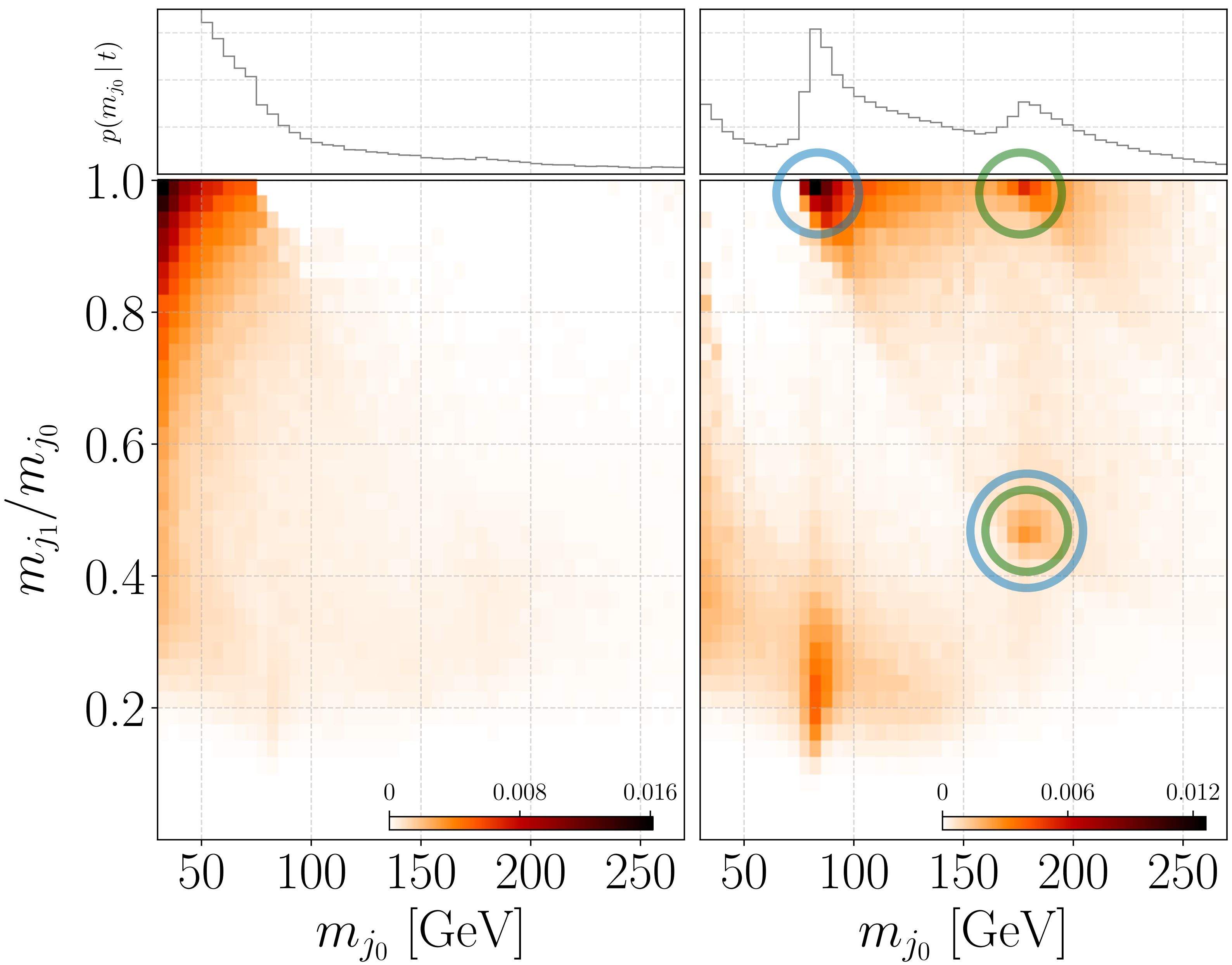

Classification of tops

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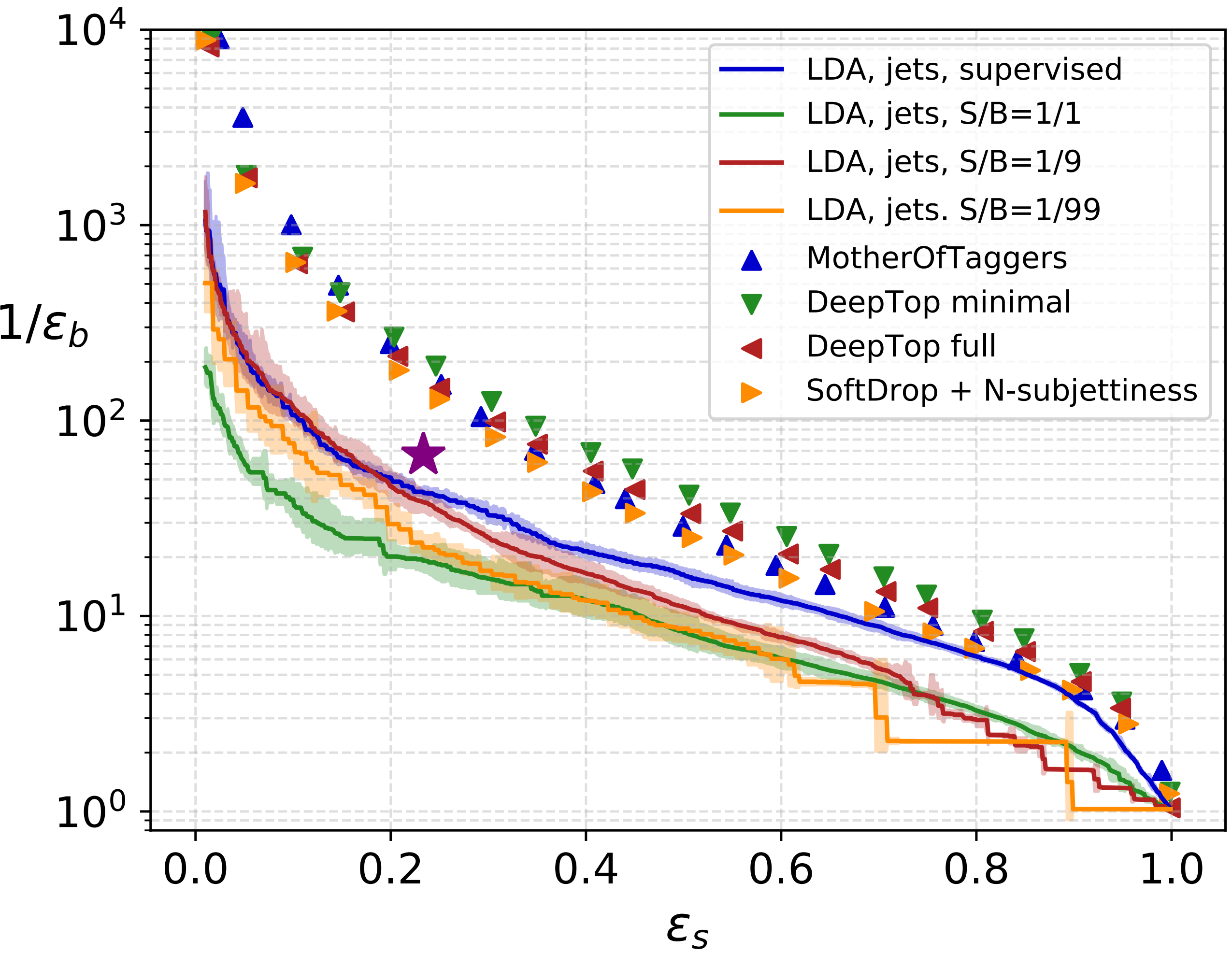

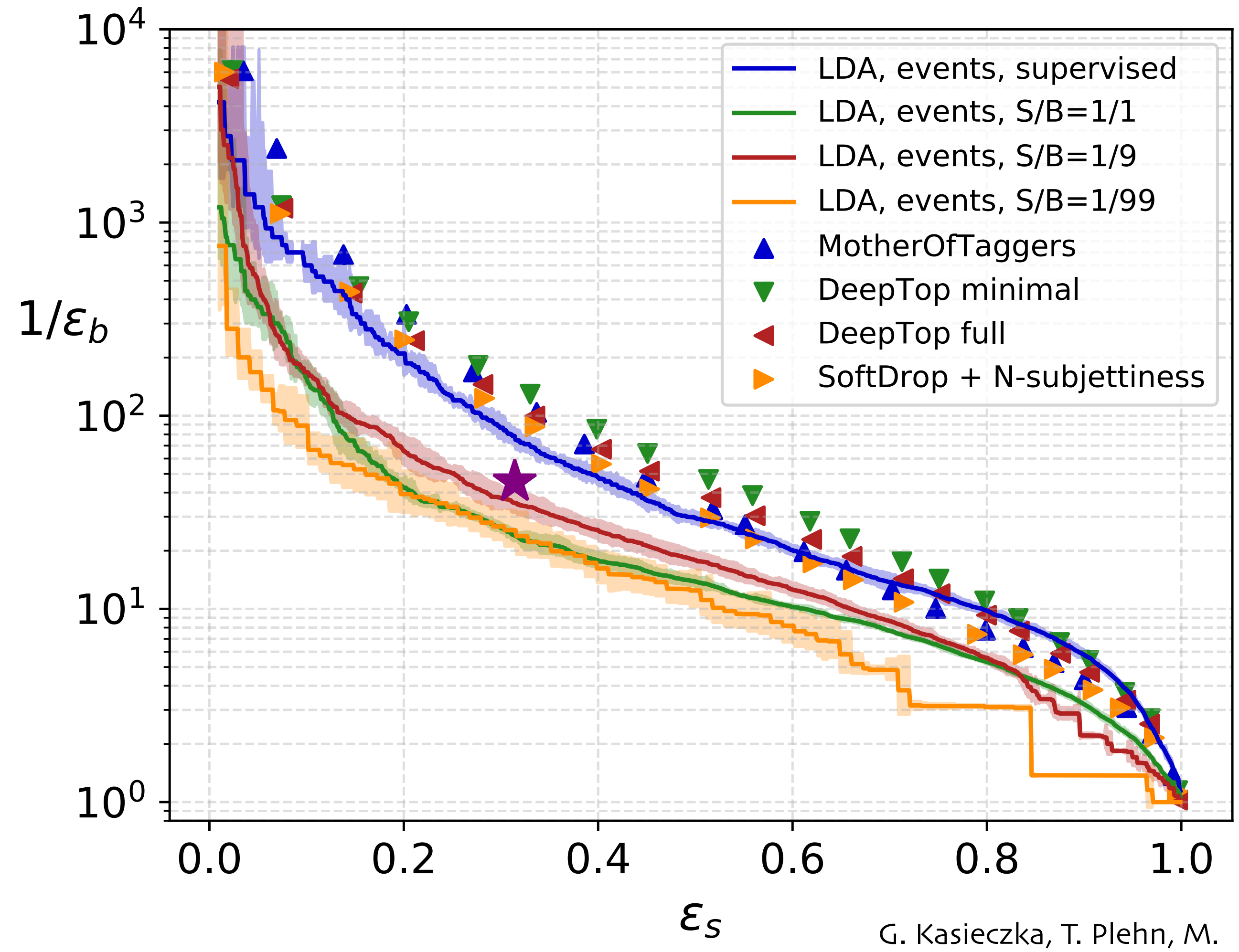

G. Kasieczka, T. Plehn, M. Russell, T. Schell (2017)

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