David Salinas

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Professional Experience

2020–Now **Senior Applied Scientist at Amazon**, *Lyon*, France
- Built an open-source Hyperparameter Optimization library that is now used in two AWS services
- Developed a transfer-learning method to learn default configurations of AutoGluon Tabular that has a winrate of 55% against current SOTA tabular methods while decreasing latency by 20%
- Introduced a new multi-objective optimization algorithm that got deployed as an AWS service and allows to recommend low cost and latency configurations for ML endpoints

2019–2020 **Senior Machine Learning Scientist at NAVERLABS Europe**, *Grenoble*, France
- Proposed an inductive bias that improves compositionality and sample efficiency of question-answering

2015–2019 **Senior Applied Scientist at Amazon**, *Berlin*, Germany
- Proposed and implemented a neural network forecasting model that got released as an AWS service
- Developed in production a forecasting model to predict labor attendance and attrition which was shown to surpass human expert accuracy and is now powering hiring decisions in all Amazon warehouses

2013–2015 **Post Doc at Inria**, *Sophia Antipolis*, France
- Coherent simplification of large 3D mesh of cities (≈6M vertices). Implementation in `C++`

Education

2010–2013 **PhD in Computer Science at Grenoble Alpes University**, *Grenoble*, France
- Proved that the Rips complex, a shape approximation used in topological data analysis, has the same topology as the shape itself given sufficiently many samples
- Design and implementation of algorithms for approximating high-dimensional shapes in `C++`

2007–2010 **BSc and MSc at Ecole Normale Supérieure de Lyon**, *Lyon*, France
- Theoretical computer science degree obtained with honours

Main Research Interests

Hyperparameter Optimization and AutoML
NeurIPSw 2019, ICML 2020, ICLRw 2020, ICLR21w, ICML21w, AutoML-Conf 2022, ICML2023

Time-series forecasting
NeurIPS 2016 (Oral), VLDB 2017, AISTATS 2019, NeurIPS 2019, IJF 2020a, IJF 2020b, JMLR 2020

Computational Geometry and Topology
CAV 2009, SOCG 2011a, SOCG 2011b, CGTA 2012, IJCGA 2012, CGF 2015, SOCG 2019

Reviewing

AutoML-Conf (area-chair). NeurIPS, ICML and ICLR (reviewer).

Best reviewer award at Neurips 2020, 2021 and ICML 2022.

Open-source

I am a core developer of `Syne Tune` (Hyperparameter Optimization), I was also a core-developer of `Gluon-ts` (forecasting), `Datawig` (data imputation) and `Gudhi` (topological data analysis).

Scientific Publication, Patent and Citation Records

Tutorials 2 tutorials given at AutoML conf

Citations 3625 citations, h-index: 19, i10-index: 24 (Google Scholar November 2023)

Publications

M. Seeger, J. Golebiowski, M. Poloczek, and **D. Salinas**. Apples and apples: Experimentation with and benchmarking of hyperparameter tuning. **Tutorial at AutoML Conference 2023**.

N. Erickson, O. Shchur, and **D. Salinas**. Autogluon v1.0: Shattering the automl ceiling with zero lines of code. **Tutorial at AutoML Conference 2023**.

D. Salinas, J. Golebiowski, A. Klein, M. Seeger, and C. Archambeau. Optimizing hyperparameters with conformal quantile regression. **ICML 2023**.

D. Salinas, M. Seeger, A. Klein, V. Perrone, M. Wistuba, and C. Archambeau. Syne tune: A library for large scale hyperparameter tuning and reproducible research. **AutoML-Conf 2022**.

D. Salinas, V. Perrone, O. Cruchant, and C. Archambeau. A multi-objective perspective on jointly tuning hardware and hyperparameters. **ICLR Workshop on NAS 2021**.

G. Zappella, **D. Salinas**, and C. Archambeau. A resource-efficient method for repeated hpo and nas problems. **ICML Workshop on AutoML 2021**.

D. Salinas, H. Shen, and V. Perrone. A quantile-based approach for hyperparameter transfer learning. **ICML 2020**.

A. Alexandrov, K. Benidis, M. Bohlke-Schneider, V. Flunkert, J. Gasthaus, T. Januschowski, D. Maddix, S. Rangapuram, **D. Salinas**, J. Schulz, L. Stella, A. Türkmen, and Y. Wang. Gluonts: Probabilistic and neural time series modeling in python. **JMLR 2020**.

T. Januschowski, J. Gasthaus, Y. Wang, **D. Salinas**, V. Flunkert, M. Bohlke-Schneider, and L. Callot. Criteria for classifying forecasting methods. **IJF 2020**.

D. Salinas, M. Bohlke-Schneider, L. Callot, R. Medico, and J. Gasthaus. High-dimensional multivariate forecasting with low-rank gaussian copula processes. **NeurIPS 2019**.

D. Salinas, H. Shen, and V. Perrone. A copula approach for hyperparameter transfer learning. **NeurIPS 2019 Metalearn workshop (spotlight)**.

J. Gasthaus, K. Benidis, Y. Wang, S. Rangapuram, **D. Salinas**, V. Flunkert, and T. Januschowski. Probabilistic forecasting with spline quantile function rnns. **AISTATS 2019**.

F. Biessmann, T. Rukat, P. Schmidt, P. Naidu, S. Schelter, A. Taptunov, D. Lange, and **D. Salinas**. Datawig: Missing value imputation for tables. **JMLR 2019**.

D. Attali, A. Lieutier, and **D. Salinas**. When Convexity Helps Collapsing Complexes. **SoCG 2019**.

D. Salinas, V. Flunkert, J. Gasthaus, and T. Januschowski. Deepar: Probabilistic forecasting with autoregressive recurrent networks. **IJF 2020**.

F. Biessmann, **D. Salinas**, S. Schelter, P. Schmidt, and D. Lange. Deep learning for missing value imputation in tables with non-numerical data. **CIKM 2018**.

J. Böse Joos-Hendrik, V. Flunkert, J. Gasthaus, T. Januschowski, D. Lange, **D. Salinas**, S. Schelter, M. Seeger, and Y. Wang. Probabilistic demand forecasting at scale. **VLDB 2017**.

M. Seeger, **D. Salinas**, and V. Flunkert. Bayesian intermittent demand forecasting for large inventories. **NeurIPS 2016 (oral)**.

D. Salinas, F. Lafarge, and P. Alliez. Structure-aware mesh decimation. **CGF 2015**.

D. Attali, A. Lieutier, and **D. Salinas**. Vietoris-rips complexes also provide topologically correct reconstructions of sampled shapes. **CGTA 2012**.

D. Attali, A. Lieutier, and **D. Salinas**. Efficient data structure for representing and simplifying simplicial complexes in high dimensions. **IJCGA 2012**.

D. Attali, A. Lieutier, and **D. Salinas**. Efficient data structure for representing and simplifying simplicial complexes in high dimensions. **SoCG 2011**.

D. Attali, A. Lieutier, and **D. Salinas**. Vietoris-rips complexes also provide topologically correct reconstructions of sampled shapes. **SoCG 2011**.

T. Dang and **D. Salinas**. Image computation for polynomial dynamical systems using the bernstein expansion. **CAV 2009**.