Predicting Depression in Old Age: combining life course data with machine learning

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Motivation

- **Population ageing** is one of the key challenges of our times. The share of the EU population above the age of 65 is expected to reach almost 25% by 2050 (starting from 19.2% in 2016).
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- Depression in old age is common. In Europe 8.9% of those among 55-64 years old and 8.6% of those 65+ suffer of chronic depression (EUROSTAT, 2019)

- Depression in old age is both under-diagnosed and under-treated in primary care setting

- Depression is an independent predictor of other major diseases: Alzheimer, dementia and diabetes
Objectives

- Prevention strategies and improvements in early identification are essential (WHO, 2016).
- Predicting depression is a challenge:
  - Lack of bio-markers/risk factors
  - Humans subjectivity
- Supervised Machine Learning Algorithms may tackle these complexities resulting in high predictive performance
- Could we preemptively identify clinically depressed individuals from their past life histories? Which is the most predictive data configuration?
- Are there differences in life course depressive patterns across genders?
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Data
- The Survey of Health, Ageing and Retirement in Europe (SHARE).
- We draw **Retrospective information** from SHARELIFE (SL) questionnaire.
- Different individuals of wave 3 and wave 7.


**Final Sample**

- Male: 27808  Female: 35218

- We select:
  1. respondents aged < 89 for recall bias.
  2. respondents that provide attention during the interview.
  3. respondents without missing variables in all depression symptoms across all waves.
Measurements framework

**Figure 1:** Measurements framework

- Educational level
- Gender
- Cohort/Age
- Country of residence
- Migrant
- Age at first childbirth
- Age at cohabitation
- Number of job changes

**Old age SWB (50-89y)**

- Depression

**Control variables**

- Socio Economic Status (SES)
- Health conditions
- School performance
- General life conditions

**Childhood events (0-15 y.)**

- Happiness/stress/financial stress/Hunger history
- Employment history
- Family history
- Health history
- Residence location history
- Housing history

**Adult life trajectories (15-49y)**
Depression in SHARE

- Depression in SHARE is measured by the 12 questions that compose the euro-D instrument: good test-retest reliability and internal consistency (Prince, 1999a).
- Clinical depression threshold: euro-D scale score of 4 or higher is categorized as case of depression (1) and a scale score below four as not depressed (0) (M. Prince et al., 1999b; E. Castro-Costa, M. Dewey, et al., 2008).
- The sample counts 24% depressed individuals (33% female, 16% male).

Figure 2: Depression prevalence across genders. Colors represent ventiles of the depression distributions in the pooled sample.
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Sequences (A. Abbot, 1995):
Sequences representations

- We construct life trajectories for 6 life dimensions:
  1. Work
  2. Family
  3. Housing arrangement
  4. Location of residence
  5. Health
  6. General life

- We operationalize sequence in three different ways:
  1. Clusters or Typologies: distinct groups of individuals’ having similar life trajectory (∼113 predictors)
  2. Sequences features: timing, duration, sequencing, and entropy (∼301 predictors)
  3. Unstructured representation (∼302 predictors)
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  2. Sequences features: timing, duration, sequencing, and entropy (~301 predictors)
  3. Unstructured representation (~302 predictors) Example unstructured
Example Features

<table>
<thead>
<tr>
<th>ID</th>
<th>Duration BC</th>
<th>Duration ST</th>
<th>Duration Rur</th>
<th>LT → BC</th>
<th>LT → Rur → BC</th>
<th>Age(20-25) Rur</th>
<th>Entropy</th>
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</tr>
</tbody>
</table>
Methods
We explore six different algorithms:

1. Logistic Regression
2. Ridge
3. Lasso
4. Elastic Net
5. Extreme Gradient Boosting
6. Artificial Neural Network
Optimization Routine

Stratified train-test split approach:

1. Training sets: 80% sample; test set: 20% sample
2. Tuning Models: random/grid search + stratified 10-folds cross validation to maximize the Area Under the Precision-Recall Curve (PR-AUC)
3. Discrimination Threshold-Moving based on the PR curve: we select the threshold maximizing the harmonic mean between recall and precision (f1-score)
4. Compare models’ performance on the test set: sensitivity and precision
Results
Sensitivity of all algorithms increases along with the increasing dimensionality of the input structure.

Setting the probability threshold at 0.42, we reach a sensitivity of \( \sim 70\% \) (from 55\%) at the cost of reducing precision to \( \sim 45\% \) (from 50\%).
SHapley Additive ExPlanation (SHAP)

- SHAP values inform on how much each input variable contribute to create the final predicted probability.

- Example: we are giving the Gradient Boosting model the life course information of a Slovenian Female of age 59, not depressed.

**Figure 4**: A SHAP force plot of a single individual. In **bold** is the predicted odd ratio, which correspond to 0.39 probability of being depressed. Red represents features that pushed the model probability score higher, blue represents features that pushed the score lower.
Depression Patterns Across Gender

**Figure 5:** Left is female and right is male. *Note:* Importance of the features in descending order of their importance based on Shapley values. Color for each feature shows the positive or negative correlation with the target outcome.

- For **both genders** and across models: age, fragile health conditions in childhood and adulthood, and low education increases depression risk.
- Only for **male** and across models: house ownership’s duration decreases the risk of depression.
- For both genders but only black box methods: higher general life entropy and no access to regular dentist increase the depression risk.
• Life histories predict some future clinically depressed individuals but are **not** able to perfectly detect them

• The data required for achieving the highest predictive performance is more complex than what has been traditionally used in well-being studies

• We identify new idiosyncratic and common patterns across genders

• Interpretable machine learning tools may support the hypothesis creation process

• **Sub-samples:**

  - Performance across gender

• **Predictions at regional levels:**

  - Predictions regional level
Thank you for your attention!
carlotta.montorsi@liser.lu
Example clusters

Figure 6: Clusters of housing arrangement, pooled sample

<table>
<thead>
<tr>
<th>ID</th>
<th>age</th>
<th>Emotion: Type 1</th>
<th>Emotion: Type 2</th>
<th>Emotion: Type 3</th>
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### Example Unstructured

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<th>Age15: Large Town</th>
<th>Age15: Small towns</th>
<th>Age15: Rural Area</th>
<th>Age15: Suburbs</th>
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Sensitivity across sub-samples

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<th>ANN</th>
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<tr>
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<tr>
<td>pooled</td>
<td>69</td>
<td>70</td>
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Conclusion
Figure 7: Left: observed depression rate at NUTS3 level. Right: aggregated depression probabilities at NUTS3