Predicting Depression in Old Age: combining Life Course data with Machine Learning

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- **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)
Motivation

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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

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- Predicting depression is a challenge:
  - Complex disease
  - Lack of bio-markers/risk factors
  - Humans subjectivity

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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- 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?
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

<table>
<thead>
<tr>
<th>Wave 1</th>
<th>Wave 2</th>
<th>Wave 3 (SL)</th>
<th>Wave 4</th>
<th>Wave 5</th>
<th>Wave 6</th>
<th>Wave 7(SL)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2004/05</td>
<td>2005/06</td>
<td>2008/09</td>
<td>2011/12</td>
<td>2013</td>
<td>2015</td>
<td>2017</td>
</tr>
</tbody>
</table>

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

- **Childhood events (0-15 y.)**
  - Socio Economic Status (SES)
  - Health conditions
  - School performance
  - General life conditions

- **Adult life trajectories (15-49y)**
  - Happiness/stress/financial stress/Hunger history
  - Employment history
  - Family history
  - Health history
  - Residence location history
  - Housing history

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

**Control variables**

- Educational level
- Gender
- Cohort/Age
- Country of residence
- Migrant
- Age at first childbirth
- Age at cohabitation
- Number of job changes
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 higher than 4 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 40% individuals with at least one depression measurement in the observation period (46% females, 29% males).
A life trajectory is defined as the long-term pattern of stability and change, which usually involves multiple transitions. Along this trajectory, each individual may experience many events, either positive or negative.
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- **Sequences** (A. Abbot, 1995):
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Sequences (A. Abbot, 1995):

![Family Trajectory Diagram]

- alone
- alone with children
- living married
- living married with children
- living with partner
- living with partner with children
- missing_family
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 events

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 (~306 predictors)
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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>
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</tr>
<tr>
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<td>0</td>
<td>0</td>
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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. Compare models’ performance on the test set: PR-AUC, AUC, Sensitivity
4. Benchmark model: minimal predictor set with only demographic information, i.e., age, interview year, migrant status, education level, age at first childbirth
Results
Models’ PR-AUC Female

Figure 3: Sensitivity across models and input structures. Performance on the test set. Female sample.

- PR-AUC of all algorithms increases along with the increasing dimensionality of the input structure.
- We reach a PR-AUC of ~ 68.2% combining the Gradient Boosting with sequential features.
For males, we reach a PR-AUC of $\sim 46.2\%$

Males’ life course trajectories are less informative than females’ trajectories.
- 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.

\[ \text{Figure 5: A SHAP force plot of a single individual. In bold is the predicted odd ratio, which correspond to 0.39 probability of being depressed. Red represents features that pushed the model probability score higher, blue represents features that pushed the score lower.} \]
Depression Patterns Across Gender

Figure 6: 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, low education, and low dental care 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 increases the depression risk.
Conclusion

- 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 thresholds
- Predictions at regional levels: Predictions regional level
Thank you for your attention!
carlotta.montorsi@liser.lu
Figure 7: 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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</table>
Sensitivity across sub-samples

Conclusion
Figure 8: Left: observed depression rate at NUTS3 level. Right: aggregated depression probabilities at NUTS3