An Approach based on State-Space Models of the Agricultural Production Risk

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Risk and Source of Risk

- The **risk** is the uncertainty or the unknown regarding an action or an activity.
- “Black Swan Theory” issued for analyze the disruptive impact of the new / unexpected occurrences (opportunities?)
  - surprise / major effect / rationalization

Agriculture – a highly risky game

- Has always been like that
- Lately, the increasing number of extreme meteorological events made this activity riskier in terms of business
- Risk sources:
  - Production/technical risk
  - Price/market risk
  - Financial risk
  - Legal risk
  - Personal risk

Risks Layers in Agriculture (OECD)

- Normal variations in production, prices and weather:
  - do not require any specific policy response
  - they can be directly managed by farmers as part of normal business strategy
- Not frequent but catastrophic events (ex. severe and widespread drought)
  - It is affecting many farmers over a wide area
  - usually is beyond farmers' or markets' capacity to cope
  - needs Government intervention

Marketable Agricultural Risks

The marketable risk layer is between the normal and the catastrophic risk layers

- The agricultural risks can be handled through market tools, such as:
  - insurance
  - futures markets
  - cooperative intervention measures

Risk aggregators

- There are two general classes of products for market-based index insurance:
  - for households - to protect against crop-yield losses due to adverse weather risk;
  - for risk aggregators - refers to firms such as lenders and agricultural value chain members who are affected (negatively) by the production risks in a geographic region

Main limitation: drought

- Romania has about:
  - 14.6 million hectares of agricultural area
  - 9.4 million hectares of arable area
- Climate: temperate-continental of transition with Mediterranean influences in SW and continental-excessive in E
- Rainfall (annual average): 600 mm in W, < 500 mm in S, < 450 mm in SE
- Severe drought frequency increasing
- Effective irrigation (2015): 145.000 hectares
- Existent irrigation facilities: 800.000 hectares
- Need (and technically possible): 1.5 million hectares

Marketable WII (Weather Index Insurance) and Selyaninov Index

- WII marketable contracts
  - come within a 20-km radius of the weather station (in many cases the applicable area is smaller).
  - Modalities must be defined for weather data collection and dissemination during the contract period
- Contracts based on Selyaninov index
  - in 40-km weather station proximity
  - calculations showed: 0.01 index points contract cover 0.03237 tons wheat production loss (ex. Braila weather station)

Selyaninov Hydrothermic Coefficient (SHR)

$$SHR = \frac{\sum Rainfall\ (t)}{0.1 * \sum Average\ daily\ temperature\ (t)}$$

Characteristics of the Selyaninov Index

- a good proxy for agribusiness losses
- data for building the index are easy to obtain
- data needed for index computing should be from reliable sources (National Authority for Meteorology and Hydrology)
- data needed for index computing should have historical presence
- In Romania, favorable weather for crops:

$$1 \leq SHR \leq 1.4$$

- < 0.6 = drought
- > 1.6 = excessive humidity

Farm Production Risk Assessment Modelling

- Non-Homogenous Hidden Markov Model involves the existence of two kind of processes:
  - Hidden processes – production loss provided by unfavorable agrometeorological production context (non-catastrophic) deeply linked with marketable index (index states).
  - The succession of index states is assumed to be stochastic and Markovian.
  - The probabilities of transitions between hidden states depend on characteristics of SHC (**Selyaninov Hydrotermic Coefficient)**
  - Observed processes - temperatures and rainfall at a fixed location, which are conditioned by the hidden process.

Probabilistic Finite State Machine

- Probabilistic finite state machine is an abstract machine used to the representation of a Markov chain, where we assume that a sequence of independent and identically distributed inputs as symbols from an alphabet chosen by agronomic meaning of Selyaninov coeficient
- if the machine is in state s_0 at time t_0, then the probability that it moves to state s_1 at time t_1 depends only on the current state
- Probabilistic finite state machine can be used as a representation of a Hidden Markov Model.

Finite State Machine Model of Hidden Market Model

- Hidden Markov Model helps us to model the crop favorability weather pattern from the crop inception (ex. wheat in mid-February) to harvest (ex. wheat harvested in the first decade of July).
- There are two states in the Hidden Markov Model, each of them coresponding to an agrometeorological situation which lead the farmer to “loss” or “win” situation (production)
- The output generated by that state is a level of index Selyaninov according to random variable for outputs accesible from that state
- The probability of given index trace can be calculated in terms of transition probabilities, which means that the level of risk exposure of the farmer’s investment will be marketable

Learning a FSM from data

- A common task arising in Machine Learning is the problem of the Hidden Markov Model inference from real production data
- The inference problem in a probabilistic graphic model consists of computing the probabilities of the hidden variables given the observations
- In the context of production risk assessment, the observations may be **Selyaninov index** values vectors and the goal of inference is to compute the probability for a particular sequence of the hidden state “loose” or “win” in crop production
- This problem can be solved with forward-backward algorithm, but the possibility to have a probability distribution over hidden states Viterbi algorithm (a form of dynamic programming) is very closely related to the forward-backward algorithm.

Further work: The Implementation with R language used in Azure Machine Learning Studio

- The learning problem for probabilistic models consists of two components:
  - learning the structure of the model
  - learning its parameters (Baum-Welch algorithm)
- **R** language package is **HMM (**Lin Himmelmann) contains:
  - Backward - computes the backward probabilities
  - baumWelch-inferring the parameters of a Hidden Markov Model via the BaumWelch algorithm
  - forward – computes the forward probabilities
  - Viterbi - computes the most probable path of states
  - simHMM - simulate states and observations for a Hidden Markov Model
  - posterior - computes the posterior probabilities for the states.

Thank you for your attention !

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