Crowdsourcing and Defence, in the age of Big Data

(extended abstract)

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1. Introduction

Crowdsourcing can be defined as "the practice of obtaining needed services, ideas, or content by soliciting contributions from a large group of people and especially from the online community rather than from traditional employees or suppliers" (Merriam-Webster Dictionary). The phenomenon as such was probably first researched by Sir Francis Galton at the beginning of the 20th century. In his seminal paper, published in Nature (1907), he demonstrated that a large group of people, containing only small percentage of experts, usually has sufficient, yet dispersed knowledge to provide correct answer to difficult questions (e.g. to predict outcome of an event).

Prediction markets are a specific type of financial markets where wagers (futures contracts) on prospective events are traded. These markets are based on the idea of crowdsourcing and employ the collective intelligence of their users. Prediction markets make use of the Bayesian interpretation of probability, introduced by Thomas Bayes, the 18th century mathematician commonly referred to as "the father of statistics" (for instance see his seminal paper Bayes et al., 1763). In doing so they use so called "the wisdom of the crowds" (Surowiecki, 2004) or "efficient markets hypothesis" (Hayek, 1945) that is also contained in the Latin phrase *Vox populi vox dei*, meaning "the voice of the people is the voice of God.

Participants of such markets give YES or NO answers to certain questions and estimate probabilities of future events in the Bayesian sense (Wolfers et al, 2004). Responses are aggregated into predictions for the areas of interest. In practice, these markets offer predictions at least as accurate as other research methods, allowing non-experts in the field to be participants of the market. The first prediction market, run with modern IT, was the brainchild of professors George R. Neymann, Robert Forsythe and Forrest Nelson who pondered whether market mechanisms could be used to predict the results of presidential elections. This idea came to life in 1988 as Iowa Electronic Markets (Wolfers et al., 2004).

At present, apart from elections and entertainment industry[1], prediction markets are widely utilised in corporate practice, mainly to monitor the status, stage, and estimated end date of projects. Market potential of innovative products can be estimated using this tool as well. Prediction markets are used by many of US corporations, e.g.: Google, Microsoft, HP, General Electric (Horn et al., 2015). Probably the first prediction market in Defence was Policy Analysis Market (PAM). In July 2003 DARPA (Defence Advanced Research Project Agency) established PAM that would allow trading in various forms of geopolitical risk and various events with global impact (Polk et al., 2003). Nowadays, the most successful prediction market in this category is Good Judgement Project run by IARPA (Intelligence Advanced Research Projects Activity) (Joseph, 2014). In Europe, as far as we are aware, there were not many prediction markets in areas like defence and high-tech, before CIAMSE, together with lndustrial Development Agency S.A. (Polish: Agencja Rozwoju Przemysłu S.A.) launched L.E.M. nano[2] in the spring of 2014. lt is the first from the set of predictions markets under L.E.M. brand. lt is devoted to high and advanced technologies with initial emphasis on carbon based nanotechnologies like ones using graphene (see www.lem-nano.pl for the latest implementation in Polish). Although the start was quite modest, the market has gained enough popularity and hence critical number of participants that allows the market to function as anticipated. At the moment the scope of L.E.M. nano is being broadened to use it for testing for high-tech niches, possible future gamechangers/flagships. ln parallel the second market called L.E.M. edu is about to be launched. The second market is focused on qualifications for a knowledge-based economy.

2. Applying prediction markets in Defence and military

As outlined in the previous section, CIAMSE has developed, in cooperation with Industrial Development Agency S.A., the first open to general public and commercially used prediction market concerned with predictions on the development of emerging technologies (L.E.M. nano). The prediction market has attracted Polish Armament Group S.A. (Polska Grupa Zbrojeniowa), resulting in an idea to apply it as dual-use technology in Defence. Such approach is inspired by *Long Range Research Development Plan*, recently announced by the Pentagon where they are seeking for major contributions from civilian technologies, like e.g. autonomous systems, algorithms, Big Data, etc.

According to our knowledge not much is known about using prediction markets in such context, especially in European NATO countries. There are only some examples of successful implementation in the US, like IARPA's Good Judgement Project or DARPA's Policy Analysis Market – both mentioned in the previous section. In addition, the ones that are known are concerned with prediction on rather strategic level. Still prediction markets' relative success in corporate practice is a clear proof-of-concept that they can be useful and hence applied to support operations in the fields for defence sector/military context that have similar operational characteristics with the business world. These include project management and at least some decision-making processes in the fields like logistics, production and R&D.

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[1] E.g. Hollywood Stock Exchange – prediction market concerned with the events related to movie industry like Oscar winners or Opening Weekends' Box Office results for released movies.

[2] L.E.M stands for Logical Extractor of Possibilities (Polish: Logiczny Ekstraktor Możliwości - L.E.M.)

Based on such observation we were tasked with development of prediction markets in three areas: "long range strategic radar" for geopolitical events, project management and decision-making support for processes in defence sector/military that share common characteristics with corporate practice[3], managing R&D including search and evaluation of new technologies applicable in the defence context.

While all of above areas are non-trivial to support with prediction markets, for the first two there exist at least some well known examples for proof-of-concept, e.g. Good Judgement Project for "long range strategic radar" and various 'success stories' from corporate world for project management and decision-making support. Still, good implementation requires solving a lot of problems, for instance market adaptation to local cultural environment/context for crowdsourcing to work properly or taking into account some specific requirements of project management in the defence sector. Another important aspect of prediction markets design is stimulating participants activity, as liquidity of the market is crucial. Hence the market participants have to be given due incentive, e.g. by creating a motivational system. One way of motivating prediction markets' users is to use gamification (for example: points, badges, leaderboards and progress bars). It turns out that such constraints have significant impact on the running of the markets, hence also on datasets produced, methods of predictive analytics that are later used and their capabilities in a particular case. Therefore we have had to solve several problems from the mechanism design domain in order to run L.E.M. nano, for instance with the use of agent-based simulations to test different approaches or used some tools from the game theory to build robust ranking system. On the sideline, it is interesting to observe that, once we completed the above task, we noticed that describing prediction markets via game theory tools is getting increasing recognition recently.

These are by no means trivial issues, but the most difficult and interesting challenge seems to be in the last area of R&D and future technologies in the defence context, as it may require extremely long predictions/projections. This is a fundamental challenge as prediction markets are proven to be good in finding anwers for the present state of things (famous Galton's problem of estimating the weight of the bull) and predicting relatively near future (see Berg et al, 2008). As for the longer time periods, they are to great extent *terra incognita* at present.

To some degree we managed to probe these uncharted waters with L.E.M. nano and now we are working to further develop methods originated on that particular market.

[3] Task is defined as thinking of all possible corporate-like processes ('everything goes' approach) that one can think of and adapt prediction markets to it ('serve all' approach). Apart from project management and production, we have especially high hope for applications to logistics.

3. Methods of generating long-term forecasts with prediction markets

One of the approaches to use prediction markets for long-term predictions is to try to fit datapoints from a prediction market into a postulated technology development growth curve.

The problem of describing technology development by certain curves has been investigated in different contexts. Examples of such curves include Moore's law and Gartner's curve presented in Figure 1 as an instance. For our case Gartner's type curves seem more appriopriate, since they distinguish important time periods in technology development and we can gather information about these milestones from a prediction market. However the transformation from the market data into the curve is not straightforward.

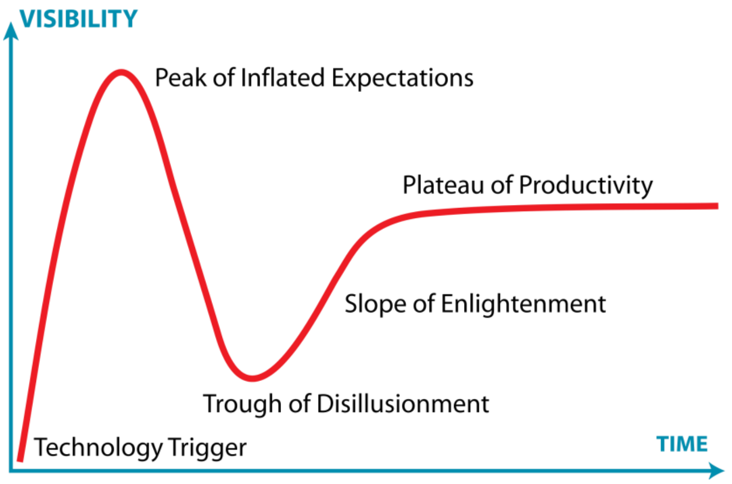

Figure 1. Gartner's hype cycle – technology development curve. (source: public domain)

There is a variety of predictive methods, classified for instance by Bruce Sterling (Sterling, 2012) in the following way:

1. consensus (e.g. Delphi method, prediction markets),
2. extrapolation (e.g. econometric models, technology growth curves),
3. historical analogy, generating paths to futurity (often by writing scenarios under different assumptions).

Many of these methods, even quantitative ones like from the field of econometrics, can be applied to the problem stated at the beginning of this section. However, when it comes to evalution, all know methods tested so far show some considerable drawbacks. Therefore we decided to develop new custom made methods.

Below we present an outline of one possible approach applied (Figure 2).

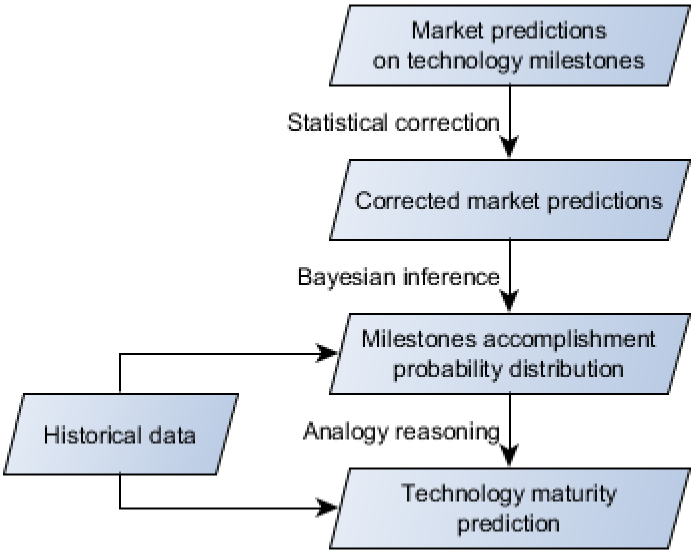

Figure 2. A general model of data flow in a prediction-market-based model for long-term predictions (source: authors).

At each step of the procedure there are challenges/problems to be addressed:

1. Statistical correction:
    a. People are prone to the favourite-longshot bias[4].
    b. At the beginning market usually needs to calibrate and stabilize, while close to the event resolution market estimates become irrelevant[5].
2. Bayesian inference:
    a. It is possible to obtain only several aggregated market predictions about a given technology milestone.
    b. Appriopriate choise of growth curves.
    c. Mapping from a discrete set of datapoints into growth curves (usually continous one).
3. Analogy reasoning:

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[4] For the analysis of favourite-longshot bias on prediction markets see for instance (Page et al., 2013) and references therein.

[5] Observed in the data from L.E.M. nano.

a. Gathering a representative set of technologies and data about their development.

There exists a variety of regression methods that can reduce the favourite-longshot bias (again see Page et al., 2013) provided that historical data from the market is available. And for this we use the data from L.E.M. nano. One approach that proved to be quite accurate in our case was by simply using regression to the following family of S-shaped curves

$$p_{a,b}(k) = \begin{cases} a\left(\frac{k}{a}\right)^{\frac{1+b}{1-b}} & \text{when } k < a, \\ 1-(1-a)\left(\frac{1-k}{1-a}\right)^{\frac{1+b}{1-b}} & \text{when } k \geq a. \end{cases}$$

Problem 1.b can be handled with the use of a proper method for aggregating individual predictions on the market. For instance it can be a weighted average of all predictions from a given period, after the stabilization phase and before the ending phase. All parameters have to be tested statistically for their fitness[6].

The idea behind the use of Bayesian inference (step 2) is that from historical data about development of different technologies we can derive a priori probability distribution related to chosen growth curves and then we can obtain a posteriori probability distributions using observables from the market. These probability distributions would then describe when consequtive milestones for a given technology would likely be accomplished.

To express this idea mathematically let us introduce x to be a random variable describing the day when a particular milestone for a technology is accomplished. We want to obtain the probability distribution for x. Let us assume that the prior distribution satisfies

$$\mu \sim N(\mu', \sigma'),$$

where μ', σ' are hyperparameters and μ is a parameter of the model – eventually the expected value of x (the expected date). The standard deviation for x is taken from historical data and is set in the model. Then the probability distribution for x is given by the posterior predictive distribution

$$x \sim p(x|m, \mu', \sigma') = \int_{\mu} f(x|\mu, \sigma)\, p(\mu|m, \mu', \sigma')\, d\mu \propto \int_{\mu} f(x|\mu, \sigma)\, L(\mu|m)\, f(\mu|\mu', \sigma')\, d\mu,$$

where p is the posterior distribution, f is the normal distribution probability density function, the values in the condition give parameters for the normal distribution, L is the likelihood and m is the market data and the knowledge that to the current date the event did not occur. But since the market data is given in terms of probabilities and not actual samples, another approach than in standard Bayesian inference is required to obtain a formula for $L(\mu|m)$. This can be done for instance with the use of maximum likelihood estimation or regression methods and such methods are still under our investigation.

The choice of historical data has to be done carefully. The idea is to gather data on different technologies (past and present) to form a representative set with the property that for every technology we analyze using the prediction market there is a subset of technologies similar to

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[6] Results have to be adequate for a given technology, but also have to be stable over technologies and time.

it. In this respect similarity has to be tested statistically against a set of relevant parameters, like the development pattern.

In the last step (3rd one) of reasoning by analogy we use only historical data. Again it is crucial to gather enough data and test it against statistical hypotheses about the similarity between different sets of technologies. Having some event of interest and a probability distribution for the milestones, we can estimate this way the probability distribution for the final product development or similar events in the maturity phase for technologies.

The procedure described above is only an illustrative example, from the variety of options, chosen to present more general approach to the solution of the problem. In reality many more tests on real data are needed to properly calibrate the procedure. They take time and hence are still underway.

4. Conclusion and further work

The development of the methods that extend time-frame of predictions/projection is far from completion. Still, results obtained so far are promising and already applicable to practical problems, hence allowing to tackle the area of R&D and future technologies in defence/military context. Hence we plan to further research the methods on theoretical grounds, while validating in practice on the prediction markets run for Polish Armament Group S.A. and possible other contractors from the field.

Same approach applies to areas of: “long range strategic radar” for geopolitical events and project management and decision-making support for processes in defence sector/military.

REFERENCES

BAYES, M., PRICE, M. 1763. An Essay towards Solving a Problem in the Doctrine of Chances. By the Late Rev. Mr. Bayes, F. R. S. Communicated by Mr. Price, in a Letter to John Canton. *Philosophical Transaction* **53**, 370-418.

BERG, J.E., NELSON, F.D., RIETZ, T.A. 2008, Prediction market accuracy in the long run, *International Journal of Forecasting*, **24**, p. 285-300

GALTON, F. 1907. Vox Populi. *Nature* **75**, 450-451.

HAYEK, F. A. 1945. The use of knowledge in society. *The American Economic Review* **35**, 519-530.

HORN, Ch. F., IVENS, B. S. 2015. Corporate Prediction Markets for Innovation Management: Theoretical Foundations and Practical Examples for Business Use. *Adoption of Innovation*. Springer, 11-23.

JOSEPH, R. 2014. Keeping Score: Better Policy Through Improved Predictive Analysis. In Proceedings of the 5th International Conference on Future-Oriented Technology Analysis.

PAGE, L., CLEMEN, R.T. 2013, Do prediction markets produce well-calibrated probability forecasts?, *The Economic Journal*, **123** (568), 491-513.

POLK, C., LEDYARD, J., HANSON, R, ISHIKIDA, T 2003, The policy analysis market: An electronic commerce application of a combinatorial information market. In Proceedings if the 4th ACM conference on electronic commerce, 272-273.

STERLING, B. 2012, The object of posteriority's scorn in Arc 1.1: The Future Always Wins, NewScientist, Reed Business Information Ltd.

SUROWIECKI, J. 2004. The Wisdom of Crowds: Why the Many Are Smarter Than the Few and How Collective Wisdom Shapes Business, Economies, Societies and Nations. Doubleday.

WOLFERS, J., ZITZEWITZ, E. 2004. Prediction markets. *Journal of Economic Perspectives* **18**, 107-126.