A predictive analytics approach to derive standard times for productivity management of case-based knowledge work: a proof-of-concept study in claims examination of intellectual property rights (IPRs)

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Algorithms, Management, Measurement, Documentation, Performance, Human Factors, Standardization.

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predictive analytics, standard times, productivity management, case-based knowledge work, intellectual property rights (IPRs).

1. INTRODUCTION

"The present letter is a very long one, simply because I had no time to make it shorter." – Blaise Pascal, 1657 [1]

1.1 The productivity challenge in knowledge work – 15 years later

About a decade after Drucker announced management's "most important contribution […] in the 21st Century" as being to "increase the productivity of KNOWLEDGE WORK and the KNOWLEDGE WORKER" [2:135], authors have noted the increasingly widespread adoption of Enterprise Resource Planning (ERP) software in Small and Medium-sized Enterprises (SMEs) [3, 4, 5]. With ERP software's requirement to structure and reengineer business processes prior to implementation [5], this development may well mark the beginning of an increasingly measurable knowledge work process for a major share of the active workforce in economies worldwide [7]. Unfortunately, merely having activities and process elements become more standardized and case-oriented (and thereby more measurable and less variable) does no equate with them becoming any more analysable per se [8]. This poses a risk to knowledge workers, as they may become susceptible to arbitrary goal setting and productivity targets exceeding the achievable – such issues have already been reported [9, 10, 11]. Likewise, employers can hardly rely on "the mysterious art and science of knowledge-worker performance" [12] to resolve itself, either – so what could be done about it?

2. TACKLING KW PERFORMANCE – A BRIEF REVIEW OF HF&E TOOLS

Human performance constraints and the fact-oriented reconciliation of employee and employer interests have been the subject of the Human Factors and Ergonomics discipline since its beginnings. It can therefore be expected to provide an ample set of tools to tackle the issues arising in deriving performance standards for a now-commonplace work form such as knowledge work – or can it? Let's briefly review the common toolsets, structured by typical sub-disciplines and common themes in ergonomics.

2.1 Industrial Engineering & office work

Beginning with Industrial Engineering, the most relevant toolsets in the productivity context are related to the analysis of work activities, the structuring of processes and the derivation of time standards for these processes. By applying these approaches, realistic performance objectives accounting for factors such as distances, weights and forces can be set through the application of predetermined time-standards (PTS) such as MTM, MOST or similar [13, 14, 15, 16].

Based on early industrialisation research [17, 18] and widely available in formats suitable for industrial application for many decades [19, 20], PTS have since then taken hold in industrial

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applications worldwide [21]. As a whole, the family of Industrial Engineering methods has been linked to US success in the arms race with Axis forces in WWII [2: 140, para. 1] and the magnitude of post-war economic recovery in Europe [2: 140, para. 2].

Some of the coarser PTS systems such as MTM-V and MTM-UAS limit the degree of task decomposition for analytic convenience, but still achieve acceptable precision [13: 523]. In a move to begin addressing the "white collar" world, they have been adapted to clerical and administrative office work (e.g. the MTM Office System), accompanied by recommendations for desk and screen work popularly associated with the term "ergonomics". Beyond this clerical-anthropometric perspective there is very little "hard number" guidance on how to organise office environments for improved knowledge work productivity and well-being.

Indeed, O'Neill & Albin [22: 2, para. 3] point out that present-day office ergonomics risks "[focussing] on only a fractional part of office work (individual discomfort and posture during interaction with a computer)", thereby "[risking] missing many opportunities to enhance the well-being and performance of office workers". According to them, "[a] 'holistic' approach to office ergonomics not only integrates the engineering and cognitive perspectives, but also expands the range of issues and workspaces addressed by the ergonomist. This broader range of issues includes informal and formal collaboration, […] group productivity and other concerns of today's interactive knowledge work".

2.2 HMI, HCI, CTA and SSTA

Things are not much better in other areas of ergonomics. Recent inventories of tools [23, 24] emphasise the human-machine / human-computer interaction (HMI/HCI) traditions of ergonomics, but yield no results in terms of knowledge work performance. The typical emphasis of these fields is on cognitive bottlenecks affecting real-time interaction with information, leading to increased cognitive loads and reduced situational awareness.

The same is true for more comprehensive techniques such as Cognitive Task Analysis [25], which provides a structured approach to knowledge work decomposition and tackling "marco-cognition" [25: 137]. Unfortunately, application examples provided in the 2006 book [25] also exclusively address work subject to real-time constraints, such as e.g. UAV operations [25: 144].

Finally, Systemic-Structural Theory of Activity (SSTA) introduced by Bedny & Karwowski [26] offers a similar, theoretically thorough framework. It links psychological approaches with manual task analysis and physiological considerations under the common umbrella of general activity theory (AT). While undoubtedly providing a rich contextual framework for analysis, the overall emphasis of SSTA is again on the micro level, favouring the fully decomposable analysis of real-time oriented tasks.

Many knowledge work tasks, however, will resist meaningful decomposition [27]. They typically take place in an environment where real-time constraints are not an issue, and this is where performance objectives (rather than workload, situational awareness and cognitive performance) pose the greatest challenge. If anything is typical about knowledge work tasks, it is that they usually allow for non-consequential deliberation and reflection, see e.g. [27: 17, para. 4].

2.3 Other streams of ergonomics

More recent applied research just about to enter the ergonomist's syllabus has similar shortcomings. For example, the field of "Service Engineering" (which one could broadly interpret as Industrial Engineering's spiritual successor for the service / knowledge economy) mostly lacks an internally-focussed, worker-centric perspective. For example, looking at a total of 29 contributions collected and published by Salvendy & Karwowski [28], only four address aspects of knowledge work and knowledge intensity in some way – but none of them from a job design perspective. The same goes for [29, 30, 31, 32, and 33].

Only the recent emphasis on "Knowledge Service Engineering" seems to offer some promise, especially "knowledge based user centred systems engineering for performance improvement" [34: ch. 20]. However, "performance" and "user-centricity" are again predominantly considered with a view to the customer and end-user of products and services, rather than with a view to the employees delivering these knowledge-intensive services.

More recent contributions from an Industrial Engineering perspective attempt to quantify aspects of knowledge work, but mainly aim at quantifying the amount of knowledge work "per se" in a given task or job [35, 36, 37, 38]. It is interesting to note that this echoes a traditional approach to job analysis, for which the importance of "informatory work" has already been acknowledged decades ago [39] and to some extent addressed with improved job-analytic techniques [40, 41]. An important contribution is the focus on aspects of knowledge work difficulty, such as [42, 43].

The broadest view taken in ergonomics sub-fields is recognizable in the macroergonomics area [44, 45]. However, its predominantly macroscopic perspective emphasises issues of organizational design and other firm-level aspects, rather than addressing task-specific considerations. More importantly, these streams have not yet found a broad reflection in ergonomics textbooks, thus limiting the visibility to practitioners.

2.4 Summing up

All in all, this mainly textbook-oriented review of the state of the ergonomic art has failed to find specific, application-oriented tools for knowledge work productivity management. It appears that much of knowledge work analysis is currently at risk of "falling through the cracks" of ergonomics disciplines. They are either concerned with cognitive processes on a microscopic, immediate interaction level between humans and their work environment (taking a "cognitive load" or a "takt" view), or with macroscopic effects in the firm-level work system. There is no immediately evident, performance-oriented guidance on how to quantify intrinsically measurable knowledge work that is neither subject to real-time constraints, nor part of an overall organisational, or process/product design issue.

Unfortunately, the proposed IEA strategy for the evolution of HF&E [46] doesn't explicitly address knowledge work, either. To some extent, this may be due to disciplinary preferences, as ergonomists tend to mostly emerge from empirically oriented in which knowledge work lacks treatment [47]. Similarly, most ergonomics work in computer science is oriented at HCI, and thereby again not overly concerned with optimisation and performance beyond "near real-time" scenarios.

3. KNOWLEDGE WORK – AMBIGUITY AND NICHE UTILITY OF A CONCEPT

3.1 Knowledge work literature: from macro-theory to the work context

Much of the long-established literature on knowledge work takes a rather broad view on the phenomenon, ranging from managerial considerations [48:122; 2, 27] to assessments in an overall societal and/or macroeconomic context [49, 50, 51, 52, 53, 54, 55, 56, 57]. While these works provide a useful backdrop for the global context in which knowledge work evolves and grows, they are also criticised for making harmful assumptions and assertions about lower-level effects on workers and jobs [47, 58, 59, 60].

More work-oriented contributions emphasise ethnographic aspects of work [61, 62, 63, 64, 65], or deliver examples of how professionals and experts think, perform, and evolve through practice [66, 67, 68]. Historically, the emergence of "Artificial Intelligence" was followed application areas of "expert systems" and "knowledge engineering", which dominated much of the 1980s and early 1990s. When these topics began to lose their broad appeal, they got complemented by Knowledge Management (KM, [69]) and Business Processes Re-Engineering (BPR, [6]).

Another decade later, Davenport [27] exhibits some consternation after years as a KM/BRM practitioner, admitting that not all structuring would function equally well for knowledge work, and that social aspects are at least equally important to success. Apart from management advice, he offers a distinction of knowledge work types from a practitioner's perspective. In the task complexity context, an academic contribution was added shortly after [42].

These examples aside, most authors remain vague about what a knowledge worker is and does. Neither Reich's "symbolic-manipulation tasks" [52] nor Drucker's "technologist" concept (adding many of the modern crafts to the knowledge work umbrella, [2:149]) provide an adequate delineation of what constitutes knowledge work and what does not. Thus reviewed across disciplinary boundaries, knowledge work is "everything and nothing" – on the one hand plausible and appealing, on the other hand muddled and elusive.[1]

3.2 The underexploited niche: knowledge work as a useful ergonomic concept

3.2.1 Utility and adoption

In spite of conceptual complications, no authors forcefully object to the notion of knowledge work's large (and increasing) prevalence. By that virtue, it appears to be a useful concept to the ergonomic practitioner, even though some of it may be difficult to observe and thus hard to quantify. A recent resurgence of the topic in Industrial Engineering supports this perception [35, 36, 37, 38]. However, IE researchers emphasise the quantification of the "degree of knowledge intensity" of given jobs or tasks.

3.2.2 The case for case-based knowledge work

Rather than following this approach, the present paper uses a different tactic to open up knowledge work for quantitative assessment. Instead of adding structure to ill-structured problems and trying to measure the degree of knowledge work at the job level, it will focus on intrinsically quantifiable "case-based knowledge work" (CBKW; recently coined in [72:64, para. 3]).

Following Davenport [27:27], this type of work could be executed by transaction workers (routine individual work), integration workers (routine collaborative work), expert workers (complex individual work) or collaboration workers (complex collaborative work), depending on the required level of expertise and/or collaboration required to resolve a given case. Presumably, the cases triggering knowledge work tasks and activities will cover a whole range of difficulty and complexity, from the simplest "standard cases" resolvable by any transaction worker (e.g. clear-cut mistakes easily identified by protocol), up to the hardest cases requiring extensive expertise and/or collaboration among experts.

The proposed case-based approach encompasses knowledge work tasks which are identifiable as discrete, measurable steps towards the resolution of cases, such as those implemented in electronic workflow systems for ERP and case management applications [72]. Brief knowledge-intensive activities "mixed into" otherwise predominantly manual tasks (such as Drucker's "technologists" would perform them) are out of scope. Instead, only tasks which will at least take a few hours (and up to a few weeks) of dedicated cognitive effort and reflection are considered. This leads to a representation of "pure", quantifiable and (to some extent) repetitive knowledge work. At the same time, real-time constraints and issues of temporary cognitive bottlenecks are mostly ruled out, unless they represent an inadequate work environment with recurring interruptions or distractions.

3.2.3 CBKW: increasingly relevant?

Some anecdotal evidence suggests that case-based knowledge work could indeed be increasingly relevant.

Firstly, there is the more and more widespread automation and IT tool support of knowledge work alluded to in the introduction. Also, instead of locally deploying expensive and resource-intensive automation tools, companies can rent these tools under "Software as a Service" (SaaS) arrangements as and when required. These systems usually offer extensive usage monitoring, sometimes as a side-effect of supporting usage-based payment schemes for smaller-scale deployments. Equipped with these monitoring tools, client companies can gain substantial insight into their global and individual usage patterns. In such constellations, every activity becomes a "case" in its own right, with time stamps permitting the detailed monitoring of productivity [27:55-56, 96].

Secondly, compliance legislation and consumer sensitivities increasingly impact modern "dot coms". Cases in point are the U.S. Digital Millennium Copyright Act (DMCA) mandating the handling of "takedown notices" [73], and the heightened EU sensitivity towards large Internet companies prominently featurings in the recent "right to be forgotten" ruling of the CJEU (Court of Justice of the European Union) [74] and the German "Street View" opt-outs (which Google implemented voluntarily) [75].

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[1] Some might argue that the ambiguity of the knowledge work concept reflects the ambiguity of modern economies. Industry sector classifications are subject to a similar "blur" with modern business models. Aero engines, for example, are increasingly sold as a service, transforming the manufacturing industry into a service provider position [70]. This is frequently encountered as a sales strategy aimed at avoiding commoditisation [71].

3.3 Tackling performance management and goal setting for case-based knowledge work

The challenge posed by case-based knowledge work becomes understandable in the context of the working assumption of this paper: with a whole range of real-world cases entering (and flowing through) a knowledge work process, their inherent measurability incurs the following risks:

1. Measuring and comparing a wide range of grossly dissimilar tasks, because counting without context is the easiest thing to implement (thus, each case closed would net a performance point, irrespective of complexity).
2. Wasting effort by misallocating cases, i.e. by allocating easy cases to experts and hard cases to newcomers.
3. Oversimplifying complex case-based knowledge work, for which suitable and adequate performance targets are harder to determine than for less complex, not as resource-critical work.

Standard times should be able to alleviate some of this complexity, as they contain the relevant "gross task duration" information for a case [14:337]. By definition, standard times therefore factor in all case-related delays (such as consultations with colleagues) in the form of allowances, making them a suitable target variable. Furthermore, time spans are of a continuous nature, and as such do not require mathematical constraints to be imposed upon the prediction result (as opposed to count data).

The practical use and application of standard data for processes is outlined in IE literature [14:431]. However, in knowledge work it is important to consider that cases are likely be dealt with in parallel, rather than serially. Therefore, standard times will frequently add up to, for example, "more than a year's work" in a given calendar year. This will need to be factored in correctively, and does not form part of this paper.

4. THE PREDICTIVE ANALYTICS APPROACH TO STANDARD TIMES

4.1 Reviewing analysis objectives

The unbiased choice of an analytical technique requires clarity about the analysis objectives. Harrell [76] describes possible objectives as:

1. "Hypothesis testing"
2. "Estimation"
3. "Prediction"

De Leeuw, in a summative foreword to Berk [77], uses slightly different terminology:

1. "Description" (one effect achieved by estimation)
2. "Prediction"
3. "Inference" (achieved through hypothesis testing)

In his later book on statistical learning [78:12], Berk extends the list to four "stories" to be told with data analysis:

1. "A Causal Story" (causally interpreted inference)
2. "A Conditional Distribution Story" (general inference)
3. "A Data Summary Story" (description)
4. "A Forecasting Story" (prediction)

For deriving standard times, the objective of obtaining an accurate prediction is dominant, followed by a basic, exploratory description of how the predictors relate to the standard time prediction. Predictive analytics clearly emphasises these objectives, while largely neglecting inferential contexts.

4.2 Characteristics of predictive analytics

In a way, predictive analytics [79] is not much more than a vogue term for techniques that are in fact already considerably older. To use Abbott's [80] description, "Predictive analytics has much in common with its immediate predecessor, data mining; the algorithms and approaches are generally the same. Data mining has a history of applications in a wide variety of fields, including finance, engineering, manufacturing, biotechnology, customer relationship management, and marketing. I have treated the two fields as generally synonymous since 'predictive analytics' became a popular term." [80:13].

It could therefore also be described by names such as data mining [81, 82], machine learning [82, 83], knowledge discovery [81], statistical learning [78, 84], pattern recognition [83], intelligent data analysis [85], algorithmic modelling [86], artificial intelligence [87], etc. The probably broadest (and newest) alternative is "data science", among others popularised by Patil [88] and Yau [89], but first introduced by Cleveland [90]. Some of these flavours are preferred by specific application domains and may indicate a preferences for certain techniques[2], but by and large they describe the same general approach – exploiting given data sets with predictive-descriptive algorithms.

Given its clear emphasis on having a predictive objective, and its untarnished reputation in other disciplines[3], predictive analytics appears to be the preferable "term du jour". It is an umbrella term for a set of model-less approaches to data analysis mainly originating in computer sciences, combined with more traditional techniques developed by statisticians. Citing Abbott once again, "Predictive analytics and statistics have considerable overlap, with some statisticians arguing that predictive analytics is, at its core, an extension of statistics. Predictive modelers, for their part, often use algorithms and tests common in statistics as a part of their regular suite of techniques" [80:10].

If anything, predictive analytics is "eclectic" and "pragmatic" in the sense Chatfield [92] describes, by applying the most adequate technique to the problem at hand, whether it be Bayesianist, frequentist or algorithmic [93]. A very integrative perspective is offered by O'Neil and Schutt, who interpret algorithm tuning parameters [94:77, para. 2] different aggregation levels of predictor variables such as business metrics [94:75] or other model constraints [94:158;205, para. 5] as Bayesian-style priors.

Predictive analytics are also fairly accessible to business applications. Business Intelligence maturity models such as [95] declare predictive analytics to be a sign of high business maturity in data

[2] "Artificial Intelligence", for example, is traditionally associated with approaches utilising Artificial Neural Networks (ANN).

[3] Among a number of econometricians, the term "data mining" has been used as a negatively connoted term for the massive automation of classical econometric techniques, and as such bears little resemblance with the set of techniques typically emerging from computer science and AI research [88].

handling, setting important incentives for companies to strive for its introduction. As a consequence, the data structures used in predictive analytics contexts resemble highly dimensional cross-tables or "data cubes" accessible to Business Intelligence practitioners [80:115]. As such, they are easily augmented by visual analytics techniques [96, 97, 98], making the autonomous generation of hypotheses accessible to industrial subject matter experts.

Last but not least, apart from forming a contemporary toolset for the quantitative analysis of data, the algorithmic modelling aspect of predictive analytics has some additional strengths to offer. Berk summarises these as "the assets of statistical learning", which can excel in the following areas [78: 332-333]:

1. Determining Functional Forms
2. Discovering Unexpected Predictors
3. Discovering Which Predictors Matter
4. Providing Useful Regression Diagnostics
5. Avoiding or Compensating for Overfitting
6. Forecasting
7. Responding to asymmetric costs
8. Exploiting Many Predictors

It's these strengths combined that make a predictive analytics approach interesting for the determination of standard times in knowledge work. After all, the determination of standard times for imperfectly understood activities requires the capability to deal with ill-structured, imperfect data formulations and approximations, such as possible/suspected predictors for case difficulty and/or knowledge worker skill.

5. STANDARD TIME DERIVATION

Following the 1940 classic "Time and motion study" by Lowry, Maynard and Stegemerten [19], it becomes apparent that their three-phase approach still has value today. In the first phase, "preliminaries", they resolve the work context in which the time study is undertaken. This is followed by the "observations" phase, during which actual execution times and expected influence factors are systematically recorded. Last, they enter the "computations and conclusions" phase, during which the standard time models are derived, augmented by the necessary allowances, and finally made available for work planning.

Translated to present-day case-based knowledge work, only minor adaptions to the three-phase approach are required:

The "preliminaries" of assessing the work context are essentially identical, and Cognitive Task Analysis [25] can serve as a suitable contemporary toolbox for knowledge elicitation. As regards the steps Lowry et al. prescribe, the "choice of operator" can safely be omitted, thanks to automatic work capture of the entire population. What cannot be omitted, however, is to attempt a "standardization" step aimed at how the knowledge work under examination is best executed. Apart from the knowledge workers themselves, typical sources of contextual information for this phase are process descriptions, standard operating procedures, operator handbooks, etc. Occasionally, a "process mining approach" can complement this initial investigation, as it allows to reconstruct actual, data-based process flows from application logs [99]. Depending on the context, this preliminary investigation can already provide performance improvements.

The "observations" are then (usually) not manually compiled, but queried from a (number of) database(s). This step offers substantial potential for data enrichment with additional predictor candidates, for which Pyle [100] offers some inspiration. The individual database query results should also be subjected to a through data quality examination, essentially using Tukey's EDA approach [101], Chatfield's IDA [102] or similar procedures [80: ch. 3].[4] Having a quantitatively oriented company culture is an asset in this context, as this usually ensures higher-quality data thanks to the many-eyes principle. Well-established and accepted metrics suspected to possess predictive value can be integrated at this stage, provided that a "leakage" risk can be ruled out.[5] Data transformations may be required at this stage, depending on the candidate predictive models and their loss functions. For example, classical least-squares regressions require a (Box-Cox) data transformation to ensure normality, whereas tree-based models are sensitive to categorical predictors of high cardinality [80:57]. At this point, the analyst must be prepared to iterate back and forth a few times between the present and the subsequent phase. However, this is frequently the case in predictive analytics projects [80:35].

Finally, the "compute and conclude" phase entails the actual model building and model performance assessment. While predictive precision is undoubtedly an important criterion, computational constrains and/or model deployment and use considerations can be just as important to build a practically useful model. This depends entirely on technical infrastructure considerations. However, can be as simple and inexpensive as equipping an analyst workstation with FOSS software, and computing only those models that provide a reasonable trade-off between computational cost and planning & optimisations benefit.[6] In case of need, the traditional "allowances" concept can also be utilised to ensure that standard times will not be underestimated – predictions likely to be affected by such negative bias could be corrected accordingly.

As this section has shown, conceptually a predictive analytics approach constitutes a good match with classical standard times. The proposed, pragmatic standards derivation concept can be expected to deliver adequate performance benchmarks for case-based knowledge work. The next section will try to provide some tangible evidence along those lines in an application context.

6. CASE STUDY & DATA PROVISION: CLAIMS EXAMINATION OF IPRs

6.1 Introducing OHIM

The Office for Harmonization in the Internal Market (OHIM), in its function as the EU Agency responsible for examining and registering Trade Marks and Designs that are valid in all EU member states, makes for an excellent field study environment for case-

[4] In the predictive analysis approach it is methodologically acceptable to explore unidimensional contributions towards the dependent variable (i.e., the execution time). This holds as long as no hypothesis testing is undertaken afterwards, as these tests would be biased [78:7, para. 5].

[5] This is where the robustness of statistical learning technique to correlated predictors comes in handy.

[6] Maynard et al. [20: 195] refer to this as "Determination of Economic Justification for [the Time] Study".

based knowledge work. Thanks to making use of ERP-like case management tools early on, it has already made substantial progress on the way to performance improvement during the past 15 years [103, 104, 105, 106].

However, past efficiency gains can mainly be attributed to management efforts directed at backlog elimination, business process re-engineering and the increased usage of case management tools to support "fully electronic" end-to-end processing of cases. As of 2014, these efforts did not involve the application of specific Industrial Engineering methods like standard times. Furthermore, all improvements were achieved relative to past performance, but no absolute benchmarks of attainable performance exist so far.

With the end of backlogs almost fully achieved in 2012, and with an already near-maximal exploitation of process-oriented Quality Management with ISO 9000 certification [107] and adaptive case management (ACM), the bulk of the "easily" attained productivity improvements is almost exhausted.

6.2 Introducing the case-handling process

As of 2014, OHIM receives about 100,000 Community Trade Mark (CTM) applications per year, 70 to 80 % of which lead to a registered CTM after a more or less lengthy process (depending on factors related to the case, and the competition characteristics of the relevant market). Aside from CTMs, applications for Registered Community Designs (RCDs) are also accepted, triggering an administratively lighter process.

Unless third parties intervene at given stages, procedures only involve the applicant and the Office's examiners, which is why they are referred to as "ex parte" procedures. If third parties get involved, or if decisions of the Office are contested, "inter partes" cases such as CTM oppositions, Cancellation proceedings or appeals[7] will emerge. It is these inter partes cases which form a process bottleneck, and for which some special measures have been undertaken (details in [108]).

6.3 Introducing the data sets

This paper will limit all treatments to the consideration of CTM opposition cases. Given their complexity and overall impact on OHIM examiner workload, they make an ideal test case for standard times derived with predictive analytics methods. Within the opposition procedure, the Office's "ex oficio decision taking" step is traditionally the most resource-intensive activity, and by that virtue most relevant for OHIM's overall operational performance.

It is triggered if the parties to the opposition case cannot reach an amicable agreement for their trademark conflict, which has been observed with increasing frequency over the past years [109]. The cases handled in this step combine a rather complex policy with large case volumes (several thousand a year). Decisions are subject to extensive randomised ex-post quality controls and frequent appeals to the decision outcome (as there is always at least one adversely affected party). As all OHIM cases, they are handled in one of the five OHIM working languages (these are in descending order of case volume: English, German, Spanish, French and Italian).

The target variable of interest for standard time derivation is the time taken from the final allocation of a case to an examiner, up to the moment the examiner closes the "decision to take" task, thereby indicating that the decision is ready for notification to the parties.

6.4 Initial data and model choices

For the presentation of first results in the next section, the population was limited to a convenience sample of 2,069 cases closed between 2009 and 2010. The sample is limited to cases closed in OHIM's latest case-handling system EuroMarc++ (introduced in February 2009), and contains German-language cases only (assuming a culturally more coherent population of parties and examiners than in English-language contexts). "Zero duration" cases have been suppressed, as these represent inadmissible cases.

To avoid "information leakage" [110], only variables known prior to the case allocation stage have been included. This excludes variables such as the case outcome, the appeal status (known only months after the decision has been notified) or the quality check result. Operational difficulty assessments are also ignored, as they are available in a limited number of cases only, unless imputated.

The final data set contains predictors related to the case and the parties (interpreted as difficulty context), the case age (interpreted as process context) and the responsible examiner's past performance (interpreted as skill context). Given its heavily categorical nature, tree-base regression models offer the greatest promise. Following comparatives [84], random forests and boosted decision stumps (gradient boosting method, GBM) seem like the most adequate choices.

To compare performance with traditional regression techniques, simple linear regression and self-tuning multivariate adaptive regression splines [111] were selected. To improve their expected performance, observed actual times were log-normalised, categorical predictors were converted to binary "dummy" variables, and all predictors underwent normalisation based on z-Scores. Other optimisations (e.g. cardinality reductions of categorical variables to reduce tree-split biases) were not undertaken. This simulates the capability of selected models to deal with data "as is", using interpretable, but redundant predictors.

Figure 1. Flow-based modelling environment (final branch).

All data preparation was executed in the KNIME open source data mining / predictive analytics toolkit [112] allowing for a flow-based data modelling approach (Figure 1). To simplify post-processing, all models were fit in the R statistical language [113].

This arrangement allows for a combination of R models with customised data transformations, replacing R's usual command line interface (CLI) with a convenient graphical user interface (GUI) for most of the processing steps. Arguably, this approach can be expected to make predictive analytics for standard time derivation more accessible to industry practitioners.

[7] While internally appeals are discerned as "ex parte" or "inter partes" appeals, they will always involve a legally separate instance, the OHIM Boards of Appeal (BoA). Therefore, in a way, all appeals are "inter partes" cases, with at least two parties able to appeal a BoA decision to EU courts in Luxembourg.

7. FIRST RESULTS

7.1 Model performance comparison

Models are assessed both as “full-model fits” and as “out-of-bag estimates” after 10 runs of 10-fold cross-validation [82:154, para. 1]. Table 1 provides an overview of goodness-of-fit (R^2), error (mean squared error – MSE) and ranked computation times.

Table 1. Basic model performance parameters (OOB: out-of-bag; estimated with 10×10-fold cross-validation)

Model	R^2	mean squared error (MSE) $[10^{-2}]$	OOB R^2	OOB MSE $[10^{-2}]$	model computation time rank (1 = fastest)
LM[8]	.602	7.74	.480	10.11	1
Reg. Sp.[9]	.617	7.45	.569	8.38	2
GBM[10]	.723	5.38	.618	7.44	4
RF[11]	.934	1.29	.639	7.03	3

Evidently, there is value to be derived from investing into computation time – in terms of out-of-bag precision, both the GBM and the RF models offer substantially better performance. As evidenced by the OOB results, gradient boosting overfits the data less, but it also takes substantially longer to compute than random forests.

On the other hand, an important benefit of GBM lies in the additional tuning potential – if considered beneficial in the application context, a GBM model can be optimised for a better balance between complexity and predictive accuracy. The same goes for tuning and search-intensive procedures like support-vector regression (SVR) and artificial neural networks (ANN), which will be examined in the near future.

However, the inspection of normalised residuals[12] in Figure 2 suggests alternatives to extensively tuned, single models. Apparently, the “average duration” cases are easy to predict with sufficient precision by simple algorithms, whereas distinctive advantages are achieved in either “fast” or “slow” cases. So instead of optimising a general purpose model, a cascaded “predictive ensemble” could classify cases into “fast / medium / slow” categories, which are then processed with bespoke, more narrowly tuned algorithms. Most of today’s data mining competitions are won by such ensemble models [94:305, para. 5], though there appears to be an effect of diminishing marginal returns at work as well [117].

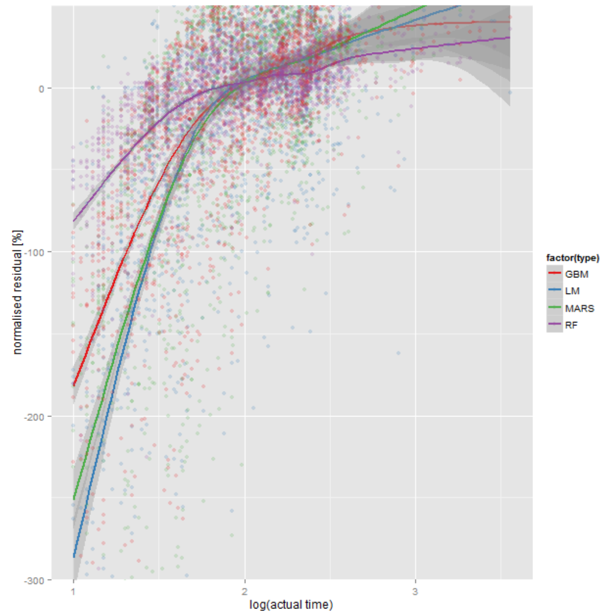

Figure 2. Normalised residuals[12] [%] of four predictive models (full-model fit) for a convenience sample of German-language opposition cases

7.2 External benchmark: predetermined time standards for manual work

Schlaich’s 1967 dissertation [118] is the most detailed treatment of the precision of various predetermined time standards, and as such provides as a suitable benchmark for similar standardisations. Except for the shortest cases, a comparison with Figure 3 suggests that the predictive precision achieved for OHIM opposition cases is roughly en par with this predetermined time standard.

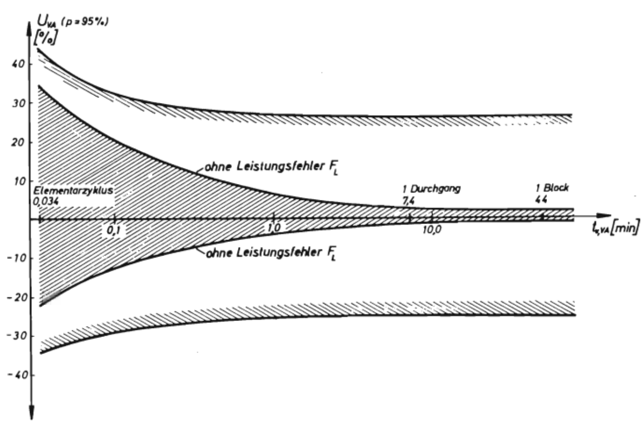

Figure 3. Accuracy of predetermined time standards for manual work [118:97] (outer boundary includes worker skill and performance variation)

In [118:75], Schlaich reports partial and overall R^2 values for full-model fits. Represented graphically, the best single worker model achieves an R^2 of approximately .70, and the best-approximated

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[8] Linear (regression) model: R package “lm”

[9] Regression splines: R pckg. “earth” (MARS® re-implemented) [114]

[10] Gradient boosting (decision stumps): R package “gbm” [115]

[11] Random forest: R package “randomForest” [116]

[12] Note the deliberate deviations from conventional, single-model residual plots: the abscissa shows actual values instead of fitted values (allowing for cross-model comparison), and the ordinate shows residuals normalised to “percent of actual”. The sign of the residual follows convention (i.e., residual = actual – prediction, meaning that negative residuals indicate overestimation and vice versa).

motion element roughly .55 across subjects ("reach"). This also compares quite favourably to the results in Table 1.

In terms of dominant factors, however, a preliminary variable importance review revealed that the case of OHIM is clearly dominated by variables related to case age and the overall process (predecessor tasks, etc.). Therefore, as far as the convenience sample is concerned, a case's history and its perceived urgency had the most substantial impact on the processing time.

This finding is consistent with expectations, since the period between 2009 and 2011 was marked by the introduction of a new case-handling system (see section 6.4 above) and an openly declared emphasis on backlog elimination (section 6.1). Moreover, the case age was featured rather prominently in the new operator user interfaces, most likely reinforcing the preferential handling of older cases. Repeated model fits with more recent data will show if the predictor importance has indeed changed to a different constellation after 2011.

In spite of the greater role of procedural handling and the comparatively lower relevance of factors related to case difficulty or examiner skill, it is nonetheless important to assess these impacts separately. A thorough model sensitivity analysis will provide such insights in the near future, alongside other model assessment tests.

8. CONCLUSIONS AND NEXT STEPS

8.1 Preliminary conclusions

As expected, predictive analytics and statistical learning methods deliver a better predictive accuracy than comparable classical regressions at a lower data pre-processing effort. This is due to specific strengths of the statistical learning models, e.g. their largely automatic, non-linear interaction handling and relative robustness to correlated predictors.

As the (initially unexpected) dominance of "case age" variables has shown, a good predictor exploitation can expose interesting relationships, thereby helping to trigger causal thinking, exploration and knowledge discovery. These features can therefore be particularly useful in ill-understood knowledge work contexts, where quantitative relationships would otherwise be hard to uncover with traditionally causally oriented, pre-specified models used for statistical inference.

While still at an early stage, model comparisons suggest that standard time prediction for case-based knowledge work is certainly feasible within acceptable accuracy. Model quality standards are promisingly high, even though no micro-level task decomposition was undertaken. Even higher prediction accuracy should be achievable with ensemble models, making present outliers eligible to improved prediction with bespoke models. Potentially, a successful prediction of inadmissible and other extraordinary cases could keep these low-value or high-stakes tasks away from specialised opposition examiners, re-routing them to administrative support staff for double-checking.

In goal setting terms, it appears that standard times could help to discriminate between "tough" and "easy" cases quite adequately, thereby helping to resolve much of the arbitrariness of "only counting cases". Deployed productively, feedback loops for "participatory ergonomics" could help achieve an even better acceptance. Implemented with "prediction response" buttons resembling SPAM/NO SPAM feedback mechanisms used for e-mail, these mechanisms could help to improve the predictive models in a similar fashion to SPAM filters.

As a whole, standard times would most likely fit quite well into an IT process analyst's toolbox. Without further modification, they provide adequate "total processing time" assessments addressing a variety of explanatory factors. However, they will likely need adjustment for individual goal setting and activity-based costing, as these will not "sum up" due to parallel processing and case alternation habits.

That said, with the large and varied range of predictive analytics, data mining and data science applications it seems likely that some similar realisations of this approach already exist in practice, but have not yet been described in literature. Given the potential for efficiency improvement from an employer's perspective, this would not come as not much of a surprise. However, it is in the best interest of affected knowledge workers subject to arbitrary goal setting to be aware of the data-based, objective alternatives presented in this paper.

8.2 A brief outlook – next steps

Next steps will comprise further models, data sets, fit refinements and assessment options, such as:

- Better data pre-processing in line with recent literature
- More derived predictors
- Exhaustive parameter search with cost/benefit review
- Sensitivity analysis, hold-out samples and year-on-year predictive performance assessments
- The inclusion of time series elements
- Ensemble models for looking into difficult-to-predict cases separately
- The addition of GLM/GAM, ANN and/or SVR models
- Adjusted R^2 and effective degrees of freedom assessments

Additionally, the inclusion of predictors collected in a semi-experimental setting described in [108] will offer additional insights of relevance to case management and knowledge worker recruitment. These predictor are:

- Operational difficulty assessments used by OHIM since 2011 [scaled as A, B, C and D cases][13]
- OP09 case data:
    - subjective difficulty assessments [9 levels]
    - psychometric trainee examiner skill/capability predictors (g factor, IPIP personality, etc.)

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