Investigating the Effects of Object-Relational Impedance Mismatch on the Efficiency of Object-Relational Mapping Frameworks

Derek Colley
Staffordshire University, United Kingdom

Clare Stanier
Staffordshire University, United Kingdom

Md Asaduzzaman
Staffordshire University, United Kingdom

ABSTRACT

The object-relational impedance mismatch problem characterises differences between the object-oriented and relational approaches to data access. This paper builds upon prior work by investigating the extent that ORM-generated queries can cause performance concerns in environments which use both object-oriented and relational paradigms, and presents a survey of database practitioners on ORM tooling and an experimental investigation into the existence and extent of operational concerns through the comparison of ORM-generated query performance and manually-written query performance on a benchmark data set. The survey results reported difficulties tuning ORM tools and distrust in their effectiveness. Through experimental testing, it is demonstrated that ORMs exhibit performance issues, confirmed by the survey results and the literature, to the detriment of the query and the scalability of the ORM-led approach. Recognising that ORMs are established in the industry, future work is outlined on establishing a system to support the query optimiser for ORM-generated queries.

Keywords: Databases, Relational Databases, Database Performance, ORM, Object-Relational, Query Performance, SQL, Performance Tuning

INTRODUCTION AND BACKGROUND

This paper sets out to investigate if Object-Relational Impedance Mismatch (ORIM) is a genuine problem affecting queries generated by Object-Relational Mapping (ORM) tools, and to investigate the existence and extent of any associated performance impacts. This is achieved in two ways: first, through the administration of a survey of practising database professionals with the aim of gathering expert opinions on ORM tooling, using thematic analysis to construct appropriate narratives; and second by investigating, through empirical experimentation and using industrial software, the existence of ORM-generated performance impacts on a relational database using a benchmark data set, extending prior research (Colley, Stanier & Asaduzzaman, 2018).

Relational databases are data stores that operate according to the long-established principles of relational algebra (Date, 1990; Astrahan et al., 1976; Held, Stonebraker & Wong, 1975; Codd, 1974; Stoll, 1963). In contrast to document-style databases, storing unstructured or semi-structured attribute-value pairs, relational database design is based on relations, or sets of related values, which are stored in tables, linked with keys and queried with SQL. It is claimed that 4 of the top 5 most popular database tools in use today are based on the relational model (Solid IT, 2018).

Object-oriented programming methods and languages have taken over from functional methods and languages. This has led to disparity between the class-method-interface model of object-oriented programming and the SQL query interface of the relational database; this disparity, termed object-relational impedance mismatch (ORIM), has been charted in the literature (Chen et al., 2014; Ireland et al., 2009) and proving the extent to which this issue can affect relational database implementations has been the focus of the authors' previous research (Colley, Stanier & Asaduzzaman, 2018; Colley & Stanier, 2017). Ireland classified the ORIM problem into four facets of a conceptual framework: paradigm, language, schema and instance. In response to the difficulties of overcoming the ORIM problem, the industrial response was development of object-relational mapping (ORM) tooling.

ORMs operate by establishing an intermediary data model between the object-oriented programming language and the relational database, and by providing an interface compatible with the programming language. The language then uses this interface by calling methods, which the ORM then translates through its internal data model and into database queries, issued against the database query engine. When the result set is returned, the ORM presents the result set in the specified format.

The remainder of this paper is structured as follows. The Literature Review section defines object-relational impedance mismatch, summarises prior research into the issue, and describes how the issue can be manifested in relational database systems. The Problem Investigation section describes the investigation; split into two sections, the Domain Expert Views sub-section explains the methodology and process of gathering domain-expert views, and presents the results; and the Empirical Investigation sub-section describes the experimental investigation into the impacts of ORM-generated queries and the results of this work. The Conclusion section draws together these results and presents the conclusions, and Future Work discusses ideas for further research in mitigating ORM-generated query performance issues.

LITERATURE REVIEW

ORMs are designed to mitigate many of the facets of the ORIM problem by the provision of an interface from the application layer to the data layer. Despite this, ORMs are reported to have pervasive performance issues which arise as an artefact of their design. Karwin (2017) labels some of these issues

‘anti-patterns’; these are undesirable behaviours of the query or queries that exhibit in several different ways.

Karwin discusses SQL anti-patterns in general but specifically identifies issues with ORM-generated queries. Models (in the Model-View-Controller arrangement) are very closely coupled with database schemata; this means changes to the schemas can result in model incompatibilities. Another related problem is inheritance; if a class is given create, update and insert capabilities, subclasses can inherit from this class which can allow direct access to the database, reducing cohesion.

It was demonstrated by Chen et al. (2014) that these anti-patterns can include the ‘N+1’ problem; this is where a query is implemented as a series of row-by-row implementations. Although this has the benefit of being memory-efficient, from a database performance perspective this can produce an unwanted number of table or index lookups (or scans, or seeks) and can lead to an exponential overhead in query processing time and resource consumption. By the designs of relational theory, set-based queries are preferred due to better efficiency and lower query cost (Karwin, 2018; Cheung et al., 2016; Fritchey, 2017; Chen et al. (2014); Date, 1990). Chen et al. (2014) also describe the eager fetching problem (‘excessive data’) where extra columnar data is brought through to the application from within the query then discarded when the results are compiled. They demonstrated a 71% increase in performance for a set of queries when mitigating this anti-pattern.

Cheung et al. (2016) repeated this finding and reported the details of how ORMs can hide this behaviour from the user, for example by using pre-fetching. The consequences of pre-fetching data include slower execution time, increased system resource use, and more data traffic. The manufacturers of ORM tools also report adverse behavioural patterns with their tools; Microsoft Corporation (2009) describe 8 different performance considerations in a popular ORM tool, Entity Framework that negatively impact query performance (7 of which occur before the query is executed). They also discuss nested queries and offer commentary on the impacts of returning large data volumes on temporary data stores and overall execution time.

Depending on perspective, the implementation of ORMs has been a mixed success. For application developers, ORMs can abstract away the maintenance of hardcoded SQL, simplifying development. Calling ORM-supplied methods rather than executing stored procedures or running inline queries is convenient and compatible with object-oriented programming languages and fits into the current *zeitgeist* of Agile, continuous-integration led application development. However, one important drawback of the model-based approach is the maintenance overhead involved in keeing the conceptual, or logical, data model and the physical data model in synchronicity, which can manifest in difficulties maintaining the code base, as investigated by An, Hu & Song (2010).

From the perspective of the database administrator, ORMs can present serious performance issues. Replacing static queries with dynamically-generated queries has inherent problems; the aforementioned N+1 and eager fetching problems (Microsoft Corporation, 2009; Astrahan et al., 1976); larger execution plans, reducing the effectiveness of the plan cache; excessive recompilations due to lack of parameterisation; the promotion of less well-performing structures like nested queries at the expense of set-theoretic constructions such as JOINs; the avoidance of advanced language constructions which could aid efficiency, such as window functions; and difficulty diagnosing access patterns (He, 2005).

Although ORM products will doubtless continue to improve in design and efficiency, some responsibility for mitigating negative performance effects of ORMs and ensuring queries can be executed in a timely and efficient manner must fall upon the relational database management system. Currently queries are disassembled, or parsed (Pachev, 2007), bound to objects, arranged into an execution plan and executed against a base schema. Although the optimiser is able to mitigate some effects of inefficient SQL query

constructions through the simplification of queries to a parse tree and a collection of heuristics, this process (the cost-based optimiser) was not designed to deal with the structures and behaviours associated with ORM-generated queries.

PROBLEM INVESTIGATION

The investigation of the problem was split into two halves; first, through a survey of database practitioners with a focus on the uses of ORM frameworks, performance tuning in database environments, and the future of relational database query performance tuning. Secondly, an experiment to determine the performance outcomes from a series of scenario-based queries was designed to compare and contrast the relative performance of queries written by a specialist and queries produced by an ORM tool. The results of both investigations are presented in this section.

Domain Expert Views

Given prior research into object-relational impedance mismatch, this section aims to investigate if ORIM presents practical issues, and if so the extent of these issues, by the administration of a survey focused on object-relational mapping tools, delivered to an audience of database practitioners.

In this section, evidence is sought as to whether ORM-produced queries, and ORMs in general, cause performance issues in real-life database environments. A survey consisting of 18 questions for an audience of database practitioners was designed, piloted and delivered with the intent to investigate several topics: the proportion of respondents who use an ORM, or use or administer database systems with ORM inputs; an estimation of the proportion of query traffic to relational database systems originating from ORMs; the experiences of the respondents in working with ORM query performance tuning, schema management, big-data-fed database systems and non-relational data stores; the beliefs of the respondents in relation to the effectiveness, compatibility and integrative ability of ORM tooling; and the opinions of the respondents on ORM-related paradigms such as object-oriented programming, Big Data, the Agile software programming methodology; object-relational (hybrid) systems and automation.

Design

The survey was designed to capture results using a mixed-methods approach. The questions were structured primarily using Likert-scaled questioning, with a mixture of qualitative free-form textual information to gather further details without placing constraints on the responses of the participants. This approach invited respondents to express their level of agreement or disagreement with a number of database-specific statements on a 5-point Likert scale with an additional neutral option added (to allow null answers to be statistically disregarded).

Delivered via the instant-messaging platform Slack to a database-specific interest group, the survey returned 19 responses. Responses were analysed as indicative samples of opinion using qualitative analysis, with free-text commentary from the respondents treated as significant and central contributions. As an alternative, the methodology of thematic analysis (Clarke & Braun, 2013; Aronson, 1995) is used to group the response data into categories and observations, create themes and formulate summary narratives.

Checks and balances were built into the survey design. Given that the research questions were well-defined before the survey was issued, some risk existed that confirmation bias would skew the results if

the questions were put in such a way as to seek affirmation of a pre-defined perspective. In mitigation, a mixture of positive and negative question forms was used when positing statements, and at several points, questions were mirrors or alternative phrasings of others already answered. This use of cross-checking was designed to measure validity, and it was found to be effective during analysis of the resulting data with few contradictions in the results.

Additionally, the survey underwent a pilot stage after which improvements were made to the internal consistency of the survey, refinement of the topics and refinement of the terminology. The survey was designed to include additional free-form text fields to ensure the capture of meaningful, context-aware qualitative information to add value, hence the use of thematic analysis. This approach was successful in uncovering additional information, useful when constructing the thematic codes.

Results and Analysis

There are several commonly-accepted stages of thematic analysis as defined by Clarke and Braun (2013), none of which are prescriptive but provide a coherent process to analysing qualitative data. The survey was designed to capture both quantitative and qualitative responses and was analysed by using all six stages of thematic analysis, from data familiarity through to thematic mapping.

The preliminary stage, in accordance with Clarke and Braun's approach, focuses on semantic analysis – the extraction of the key information about what is said, or written, rather than latent analysis of the underlying meaning. The responses from the survey were analysed in this way, resulting in a preliminary codification of the data.

In the next phase, refinement of the codes and re-arrangement of the themes took place in order to simplify the findings. This was accomplished by de-duplicating codes, re-arranging them into a different configuration of themes, and rephrasing the codes to remove unnecessary detail. At this stage, latent analysis began to take prominence over semantic analysis. Table 1 shows the outcome of this phase.

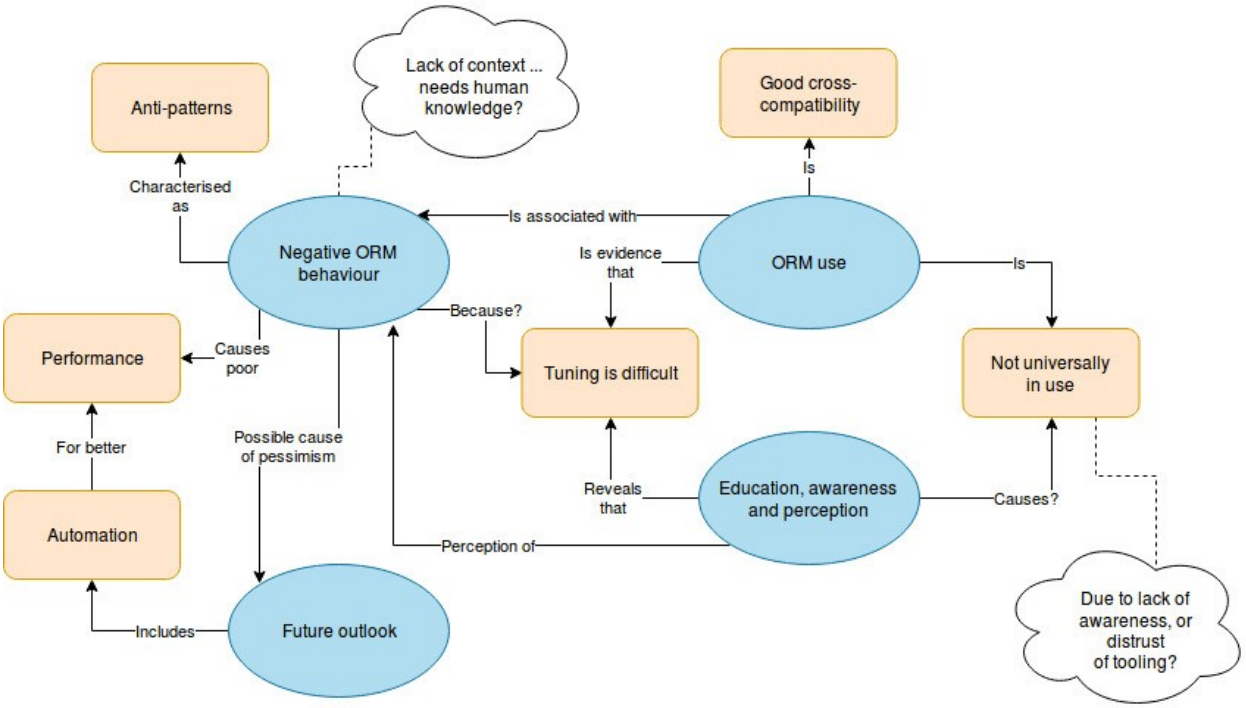
Table 1. Final codification of the survey data

ORM use	**Negative ORM behaviour**
Minority proportion of query traffic generated from ORMs	Parameter sniffing
ORMs not used across all organisations	Poor execution plans
Big data performance tuning not integral part of roles	Eager fetching
Compatible with scalable schema designs	Procedure cache misuse
Difficult to reproduce performance issues	N+1 row fetching
Challenges when designing against ORMs	Indexes not considered or supplied
	Lazy loading
Education, awareness and perception	Nested queries
DBAs have fewer skills in big data administration	No contextual awareness
Lack of awareness in ORM internals among professionals	**Future outlook**
Lack of awareness of native database tools among developers	Lack of belief in ORMs as viable future technology
Traditional tuning methods well understood	Automation believed to be beneficial, with caveats
ORMs perceived as difficult to tune effectively	Lack of belief that automation of query tuning is achievable

Perception that ORMs exhibit poor performance	Performance as important to viable future DB systems
ORM query tuning perceived as difficult	Flexibility is less important than other components

Next, by examining the codification and theme groupings, simplifications and linkages of the concepts resulted in the interpretative creation of a thematic map. Links are drawn between concepts to show the interplay of the themes. Figure 1 shows the thematic map with themes as ellipses, sub-themes as rounded rectangles, and the links and insights associated with them.

Figure 1. Thematic map of survey results



The final stage was to construct narratives from the thematic map, using the notarised codes as supporting material. These narratives are presented below, and draw from the codifications, thematic map and the supporting literature.

Theme - ORM Use

The results showed that ORM uptake amongst organisations linked to respondents in the survey is approximately 60% and of those, around 25% of traffic is thought to originate from ORM tools. Consequently ORMs are responsible for a sizable minority of query traffic. ORMs are held to be generally compatible with database scalability designs such as normalisation, but notably incompatible with some features of the RDBMS, such as re-use of plans within the procedure cache, good matching with indexes, and adherence to query structures that create efficient execution plans (such as JOINs).

The use of ORMs could be evidence that tuning databases and database queries is difficult, with the path of least resistance seen as the use of ORMs to abstract query design to an interface layer, although this finding is countered by some evidence from the comments received in the survey that there are design and interaction difficulties inherent when interfacing with ORMs, backed up with the paradigmatic differences outlined by Ireland et al. (2009). The difficulties of tuning ORMs is reinforced by a general perception amongst practitioners (67% detracting views) that this is the case, alongside the negative consequences (anti-patterns) that arise when using them.

Theme - Education, Awareness and Perception

There is some evidence of the view that the perceptions of ORMs as being difficult to tune are reinforced by a lack of awareness of how ORMs operate, or how they are configured, and that mutually the lack of awareness and education (of both administrative practitioners and users, or developers) contributes to the misconfiguration of ORMs – 82% of respondents had 3 or more years of experience, but only a third use ORMs regularly in their roles. There is a widespread perception that ORMs cause negative performance implications evidenced in both the free-form text responses and the statistics (no respondents agreed that ORMs were straightforward to tune), with numerous examples provided, and this could contribute to the minority use of this technology.

The responses suggest that the proliferation of ORM tools is in part consequential to a lack of awareness amongst the development community of the native tooling available within relational database management systems; for example, the use of stored procedures as interfaces, or queue-based messaging systems built into the product suite. However, this view could be biased by a cultural perception, evidenced in literature (Ambler, 2018; Ambler, 2008), of a disconnection between development and administrative technical communities, manifest by the administrative audience of the survey.

Theme - Negative ORM Behaviour

The chief finding was that query anti-patterns are held to be the causes of poor query performance in the database layer, and that this is exacerbated, with reference to the other themes, by a lack of awareness in database performance optimisation amongst developers, by lack of awareness of the native features of RDBMS systems, and by the difficulty of tuning ORM tooling. The exhibited (or perceived) behaviour of the ORM tools correlated with a generally pessimistic view of the role of ORMs in the future of database interaction, although contradicted somewhat by support for further automation. It is noteworthy that although 57% of respondents agreed automation had a role in the future of database performance tuning, only 8% (2 respondents) agreed that ORMs formed part of that role.

Theme - Future Outlook

Automation of query- and database performance tuning was suggested both by the measured question responses and by ad-hoc suggestions in free text responses, building on prior work in the literature addressing more effective database workload management (Niu, Martin & Powley, 2009). It was felt that the future of performance tuning was underpinned by automation, although emphatically not by ORMs. This suggests that ORMs are perceived to have reached a peak performance level, and that the future of database interaction may lay in a different direction.

Several core concepts, such as performance, confidentiality, availability and flexibility were rated for importance on a scale of 1-10, with 10 as the most important. One notable result was that performance was rated at 8 out of 10, and flexibility at 6 out of 10, indicating performance to be a more important issue than flexibility, despite a flexible approach being desirable to deal with ORM-related queries.

In conclusion, the survey indicated that ORMs are distrusted among database practitioners; that there is a perception, backed by anecdotal evidence, that ORM tools create performance tuning problems; that there is an appetite for more automation in performance tuning and database management; that practitioners felt there is a lack of awareness among developers around effective ORM use; and that ORM uptake is significant enough in industry for ORM-generated query tuning to be an important and timely research issue.

Next, an investigation was carried out into whether performance issues reported by the survey can be replicated through experimentation with an industry-standard ORM tool.

Empirical Investigation

The purpose of the experimental validation is to investigate whether ORM tools may generate queries which have adverse performance effects when compared to queries written by a subject matter expert. This stage was designed to triangulate upon the findings of the survey-based problem validation, investigating empirically whether the conclusions reached are borne out in the results of ORM query generation.

Test Data

For testing, the El Nino data set from the Pacific Marine Environmental Laboratory in Seattle, Washington, USA (Pacific Marine Environmental Laboratory, 2018) was chosen as it contains a selection of multivariate data that lends itself to reformatting without loss of integrity and is recognised as a benchmark data set used for data mining (Bay et al., 2000), ensuring repeatability. This data set contains weather data readings recorded by a series of 70 buoys spread across the Atlantic Ocean between 1980 and 1998 and is presented as a single comma-separated values file with 178,080 rows and 2,136,960 data points spread across 12 attributes.

Configuration Methodology

The data was imported from a comma-separated format to a single table in Microsoft Azure DB, then normalised to 3NF to provide the advantage of simulating multi-table queries, and each column was assigned an appropriate data type. For the ORM layer, Python was configured with the Django web framework which includes the ORM tool *Django ORM*. The package *django-pyodbc-azure* was used for Azure DB database connectivity and a new model was generated from the 3NF schema. A new property and function were created for the *distance* measurement required by one of the query objectives, detailed in the discussion of query objective O5.

Aim, Objectives and Variables

The aim of this set of tests is to examine the differences between queries generated by a subject matter expert and queries generated by an ORM tool, and note which, if any, structural anti-patterns (Karwin, 2017; Ireland et al., 2009) are observed.

The objectives of this experiment were to determine whether:

1) The performance of ORM-generated queries tends to be inferior to manually-written queries when comparing execution speed, resource consumption and execution plan complexity;

2) ORM-generated queries demonstrate poorer relational query construction than queries constructed by a subject matter expert; specifically, whether ORMs tend to generate queries which have redundancies, are loop- rather than set-based, or display other inefficient characteristics as detailed elsewhere in the literature.

The evaluation criteria used were based upon quantifiable and measurable instruments, and were chosen as accurate representations of how queries are assessed by professionals (Fritchey, 2017). Each criterion is composed of an independent variable ('measure') whose value changes upon the manipulation of the dependent variable, and a description indicating how the criterion should be assessed ('comparative rule'). The criteria are also defined and described fully in Fritchey (2017) and summarised in Table 2.

Table 2. Measures (independent variables) to compare the efficiency of queries

Measure	Definition	Comparative Rule
Cached plan size (B)	The size of the cached plan in bytes.	Smallest plan
Total plan cost	Relative measure expressed as a real number.	Lowest plan cost
Compile time (ms)	Time in milliseconds to compile the plan (ready for execution).	Shortest compile time
Memory used during compilation (B)	Memory that was used (B) to compile the plan.	Lowest memory use
Memory required (KB)	Memory that was required to execute the query (KB).	Lowest memory use
Memory requested (KB)	Memory that the query optimiser requested to be reserved to execute the query (KB).	Most accurate (to Memory Required)
Total execution time	The time taken, in ms, between the query being executed and the return of the result set.	Shortest execution time
Total count of queries	The total number of separate SQL queries required to achieve the object.	Fewest number of queries

The validity of objective 2, whether ORM-generated queries exhibit anti-patterns, is addressed through the comparison of each SQL query pair, noting any anti-patterns that emerge, cross-referencing against the performance analysis where appropriate and sources of query anti-patterns in the literature, and cases where query functionality is missing in the ORM.

The objectives described in Tables 3.1 to 3.5 represent queries against the data and are rendered firstly in English, then as a relational SQL query written by a practitioner; as a Django ORM method call; and as

one or more relational SQL queries produced by Django ORM as a result of the method call.

Table 3.1. Query Objective O1

Descriptor	Values
Summary	Return the mean average air temperature for all buoys on a month-by-month, year-by-year basis, ordered by month and year ascending.
Manual SQL	SELECT [dimDate].[mthNum], [dimDate].[yrNum], AVG([factTAO].[airTemp]) AS [airtemp__avg] FROM [factTAO] INNER JOIN [dimDate] ON ([factTAO].[dateKey] = [dimDate].[dateKey]) GROUP BY [dimDate].[mthNum], [dimDate].[yrNum] ORDER BY [dimDate].[mthNum] ASC, [dimDate].[yrNum] ASC
Python/Django	`FactTAO.objects.all().select_related('datekey').values('datekey__mthnum', 'datekey__yrnum').annotate(Avg('airtemp')).order_by('datekey__mthnum', 'datekey__yrnum')`
ORM SQL	SELECT [dimDate].[mthNum], [dimDate].[yrNum], AVG(CONVERT(float, [factTAO].[airTemp])) AS [airtemp__avg] FROM [factTAO] INNER JOIN [dimDate] ON ([factTAO].[dateKey] = [dimDate].[dateKey]) GROUP BY [dimDate].[mthNum], [dimDate].[yrNum] ORDER BY [dimDate].[mthNum] ASC, [dimDate].[yrNum] ASC

Table 3.2. Query Objective O2

Descriptor	Values
Summary	Return the earliest and latest dates for which buoy sensor readings exist within the data set.
Manual SQL	SELECT MIN(f.dateKey) [earliestDate], MAX(f.dateKey) [latestDate] FROM dbo.factTAO f
Python/Django	`FactTAO.objects.aggregate(Min('datekey'), Max('datekey'))`
ORM SQL	SELECT MIN([factTAO].[dateKey]) AS [datekey__min], MAX([factTAO].[dateKey]) AS [datekey__max] FROM [factTAO]

Table 3.3. Query Objective O3

Descriptor	Values
Summary	Return the latitude and longitude positions of all buoys in January 1984, with no ordering.
Manual SQL	SELECT f.obsID, l.lat, l.long FROM dbo.factTAO f INNER JOIN dbo.dimLocation l ON f.locationKey = l.locationKey INNER JOIN dbo.dimDate d ON f.dateKey = d.dateKey WHERE d.yrNum = 1984 AND d.mthNum = 1
Python/Django	`FactTAO.objects.select_related('dimlocation__locationkey').all()` `.select_related('dimdate__datekey').all().values('obsid', 'locationkey__lat', 'locationkey__long').filter(datekey__mthnum = 1, datekey__yrnum = 1984)`
ORM SQL	SELECT [factTAO].[obsID], [dimLocation].[lat], [dimLocation].[long] FROM [factTAO] INNER JOIN [dimLocation] ON ([factTAO].[locationKey] = [dimLocation].[locationKey]) INNER JOIN [dimDate] ON ([factTAO].[dateKey] = [dimDate].[dateKey]) WHERE ([dimDate].[mthNum] = 1 AND [dimDate].[yrNum] = 1984)

Table 3.4. Query Objective O4

Descriptor	Values
Summary	Analyse sea surface temperature during the year 1990, and return all rows, including missing data, indicating as anomalous all values where the sea surface temperature is further than 2.5 standard deviations from the average for the year, ordered by date ascending.
Manual SQL	SELECT d.dateKey, f.obsID, f.seaSurfaceTemp, CASE WHEN f.seaSurfaceTemp IS NULL THEN 'Data missing' WHEN ABS(f.seaSurfaceTemp - sd.[avg]) > (2.5 * sd.sd) THEN 'Anomalous' ELSE 'Normal' END [isAnomalous] FROM dbo.factTAO f INNER JOIN dbo.dimDate d ON f.dateKey = d.dateKey CROSS JOIN (SELECT AVG(f.seaSurfaceTemp) [avg], STDEV(f.seaSurfaceTemp) [sd] FROM dbo.factTAO f INNER JOIN dbo.dimDate d ON f.dateKey = d.dateKey WHERE d.yrNum = 1990) sd WHERE d.yrNum = 1990 ORDER BY d.dateKey ASC

Python/Django	`aggs = FactTAO.objects.select_related('datekey').filter(datekey__yrnum = '1990').aggregate(Avg('seasurfacetemp'), StdDev('seasurfacetemp'))`
	
	`outer = FactTAO.objects.select_related('datekey').values('datekey', 'obsid', 'seasurfacetemp', isAnomalous = Case(When(seasurfacetemp = None, then = Value('Data Missing')), default = Value('Normal'), output_field = CharField() )).filter(datekey__yrnum = 1990).order_by('datekey')`
	
	`for i in outer:`
	`if abs((float(i.get('seasurfacetemp') or 0) -`
	`aggs.get('seasurfacetemp__avg'))) > 2.5 *`
	`aggs.get('seasurfacetemp__stddev') and (i.get('isAnomalous') != 'Data Missing'):`
	`i['isAnomalous'] = 'Anomalous'`

ORM SQL	(@P1 int) SELECT AVG(CONVERT(float, [factTAO].[seaSurfaceTemp])) AS [seasurfacetemp__avg], STDEVP([factTAO].[seaSurfaceTemp]) AS [seasurfacetemp__stddev] FROM [factTAO] INNER JOIN [dimDate] ON ([factTAO].[dateKey] = [dimDate].[dateKey]) WHERE [dimDate].[yrNum] = @P1 (@P1 nvarchar(24),@P2 nvarchar(12),@P3 int) SELECT [factTAO].[dateKey], [factTAO].[obsID], [factTAO].[seaSurfaceTemp], CASE WHEN [factTAO].[seaSurfaceTemp] IS NULL THEN @P1 ELSE @P2 END AS [isAnomalous] FROM [factTAO] INNER JOIN [dimDate] ON ([factTAO].[dateKey] = [dimDate].[dateKey]) WHERE [dimDate].[yrNum] = @P3 ORDER BY [factTAO].[dateKey] ASC

Table 3.5. Query Objective O5

Descriptor	Values
Summary	Return the approximate distance in miles between the two buoys that were furthest apart on 01 May 1994, ignoring missing data.
Manual SQL	;WITH locationData AS (SELECT f.obsID, d.dateKey, l.lat, l.long FROM dbo.factTAO f INNER JOIN dbo.dimLocation l ON f.locationKey = l.locationKey INNER JOIN dbo.dimDate d ON f.dateKey = d.dateKey WHERE d.dateKey = '1994-05-01'), allCombinations AS (SELECT l1.obsID [from], l2.obsID [to], l1.lat [fromLat], l2.lat [toLat], l1.long [fromLong], l2.long [toLong] FROM locationData l1 CROSS JOIN locationData l2), distances AS (SELECT c.[from], c.[to], c.fromLat, c.fromLong, c.toLat, c.toLong, MAX(ACOS(SIN(c.fromLat)*SIN(c.toLat) + COS(c.fromLat)*COS(c.toLat)*COS(c.toLong - c.fromLong)) * 3958.75) [d] FROM allCombinations c GROUP BY c.[from], c.[to], c.[fromLat], c.[toLat], c.fromLong, c.toLong) SELECT TOP 1 CAST(d.d AS NUMERIC(16,2)) [MaxDistance] FROM distances d ORDER BY [d] DESC

Python/Django	from django.db.models import Max
	import math
	
	locationData = FactTAO.objects.select_related('datekey',
	'locationkey').values('obsid', 'datekey', 'locationkey__lat',
	'locationkey__long').filter(datekey = '1994-05-01')
	
	locationDataList = list(locationData)
	vals = []
	for i in locationDataList:
	vals.append(list(i.values()))
	allCombinations = []
	for i in range(0, len(vals)):
	for j in range(0, len(vals)):
	r = dict({"from":vals[i][0], "to":vals[j][0], "fromLat":vals[i]
	[2], "toLat":vals[j][2], "fromLong":vals[i][3], "toLong":vals[j][3]})
	allCombinations.append(r)
	
	for row in allCombinations:
	LocationDataTempTable(fromField = row.get("from"), toField =
	row.get("to"), fromLat = row.get("fromLat"), toLat = row.get("toLat"), fromLong
	= row.get("fromLong"), toLong = row.get("toLong")).save()
	
	all = LocationDataTempTable.objects.all()
	dists = []
	for i in all:
	dists.append(i.distance)
	max(dists)

ORM SQL	declare @p1 int set @p1=NULL exec sp_prepexec @p1 output,N'@P1 nvarchar(20)',N'SELECT [factTAO].[obsID], [factTAO]. [dateKey], [dimLocation].[lat], [dimLocation].[long] FROM [factTAO] INNER JOIN [dimLocation] ON ([factTAO].[locationKey] = [dimLocation].[locationKey]) WHERE [factTAO].[dateKey] = @P1',N'1994-05-01' select @p1 (the following query is repeated 1,156 times with different parameters) declare @p1 int set @p1=NULL exec sp_prepexec @p1 output,N'@P1 int,@P2 int,@P3 float,@P4 float,@P5 float,@P6 float',N'SET NOCOUNT ON INSERT INTO [locationDataTempTable] ([from], [to], [fromLat], [toLat],

	[fromLong], [toLong]) VALUES (@P1, @P2, @P3, @P4, @P5, @P6); SELECT CAST(SCOPE_IDENTITY() AS bigint)',997,997,46.064999999999998,46.064999999999998,57.380000000000003,57.380000000000003 select @p1 SELECT [locationDataTempTable].[uqid], [locationDataTempTable].[from], [locationDataTempTable].[to], [locationDataTempTable].[fromLat], [locationDataTempTable].[toLat], [locationDataTempTable].[fromLong], [locationDataTempTable].[toLong] FROM [locationDataTempTable]

The non-ORM generated queries were written manually by a subject matter expert to meet the query objectives before using Django ORM to generate queries that would meet those objectives. The underlying database objects via the Django ORM were accessed by opening a Django shell in Python then calling the methods in the *models* module of the new application and tracing the queries against the database using a profiling tool. This enabled the comparison of the manual database queries with the ORM queries to determine if there were any differences which might impede performance.

Experimental Results

Table 4 shows how the manual SQL (non-ORM) queries compare with the ORM-generated queries for the 7 independent variables used as measures.

Note that due to random fluctuations in the compile time and total execution times that were outside the control of the experiment (including network latency to the database server; worker availability on the CPU scheduler; and memory allocation delays) a total of ten executions, with forced recompilation to avoid plan re-use, for each test were conducted to mitigate these effects and the mean average results (denoted as μ) are shown. Where there are multiple queries, the sum of the iterations are given under each measure heading.

Table 4. Results from ORM-generated and manual query performance testing

	Cached plan size (KB)		*Total plan cost*		*μ Compile time (ms)*		*Memory used during compilation (B)*	
	Non-ORM	**ORM**	**Non-ORM**	**ORM**	**Non-ORM**	**ORM**	**Non-ORM**	**ORM**
O1	80	72	2.59791	2.59791	14.8	13.4	376	376
O2	16	16	1.51565	1.51565	1.0	1.4	216	216
O3	72	64	2.42003	2.42003	2.0	9.4	512	512
O4	96	128	5.24644	5.25825	17.4	24.2	776	856
O5	56	64	3.37822	13.08612	16.0	4.0	1344	472
	Memory required (B)		*Memory requested (B)*		*μ Total Execution Time (ms)*		*Total number of queries*	
	Non-ORM	**ORM**	**Non-ORM**	**ORM**	**Non-ORM**	**ORM**	**Non-ORM**	**ORM**
O1	2048	2048	3152	3152	1482.0	1484.0	1	1
O2	0	0	0	0	537.6	596.4	1	1
O3	3240	3240	3240	3240	449.0	572.2	1	1
O4	3712	5704	3712	5704	1942.4	1829.8	1	2

O5	1736	0	1736	0	98.0	32441.0	1	1,158

Query Objective O1

The queries were non-identical. The ORM tool produced a near-identical structural query but with the addition of an explicit CONVERT() operation on the airTemp column. This conversion was not required since the column was already stored in the FLOAT datatype. This difference was absorbed by the query optimiser ignoring the conversion request which resulted in identical query plans.

Anti-pattern(s): *Redundant code*

Query Objective O2

Note that *aggregate()* returns a dictionary object, not a QuerySet object. The *annotate()* method is not suitable when there is no column to group by.

The queries were structurally identical with very small differences in the alias names and whitespace. This was reflected in the identical query plans, although the ORM-generated version took slightly longer to compile and execute, possibly due to a minute addition to the delay in the parsing stage by the different syntax.

Anti-pattern(s): *None*

Query Objective O3

The queries were structurally similar, with aliasing differences and transposition of the predicates in the WHERE clause. Although different query plans were used, their key metrics were identical. Of small note is how the ORM tool generated needless syntax (brackets) and did not alias the columns. Execution time was inconclusive, with the non-ORM version registering a longer execution time but the ORM version taking longer to compile.

Anti-pattern(s): *Redundant code*

Query Objective O4

Django ORM does not support the creation of Cartesian (CROSS) JOINs against the data model. Instead, a more creative solution is required. The mean average and standard deviations of the data were collected and stored as dictionary entries in memory, then the main query results similarly. The *isAnomalous* column of the main results was updated depending on the average and standard deviation values, and whether the data was missing (NULL). This overcame practical difficulties working with the *NoneType* (NULLable *QuerySet* column) when trying to convert to float. However, for a fair comparison to the SQL version, the time taken to update this *QuerySet* in memory was added. Consequently, the ORM equivalent became a three-step process.

The queries and subsequent plans produced for this query pair were extremely divergent. Due to lack of full ANSI-SQL syntax support (identified here and indirectly by Ireland et al. (2009)), the approach

needed to solve the problem and the consequent queries produced were correspondingly different. The ORM-generated query also demonstrated a redundant CONVERT(), as in objective O1, but did demonstrate use of the native query preparation tools to handle the parameters and avoid storing the values with the compiled plan, which would increase the likelihood of parameter sniffing in future iterations and consequently skewed data affecting plan efficiency. As shown by the performance measurements, the ORM-generated query displayed significantly worse performance in many terms.

Anti-pattern(s): *Lack of full ANSI-SQL syntax support, redundant code, multiple queries*

Query Objective O5

The database query is too complex for the Django ORM to replicate directly, since it doesn't support CROSS JOIN and there is limited support for the COS, ACOS, SIN and ASIN functions. Instead, the ORM was used to extract the location data, which was consumed recursively by iterating over each row in the location data for each row in the query set, effectively recreating a CROSS JOIN. The *distances* CTE was then compiled using a custom *distances()* function in the class definition using methods from the *math* module to implement the logic. Finally, the max aggregation of the output of this function was returned to the console.

This set of calculations is an implementation of the spherical law of cosines, scaled for miles, to calculate distance between two points on a sphere ('Spherical Trigonometry', n.d., para. 6). This was used to accurately measure distance while taking into account the curvature of the Earth.

Observations included 1,156 individual INSERT queries ran in place of a single INSERT, the splitting up of the query into multiple queries, double writes to the database, redundant code and implicit conversion issues. Although some metrics such as plan size were smaller than non-ORM generated queries, the query execution time for the ORM query was more than 300x that of the non-ORM query.

Anti-pattern(s): *Multiple queries, N+1, implicit conversion, redundant code, lack of ANSI-SQL support*

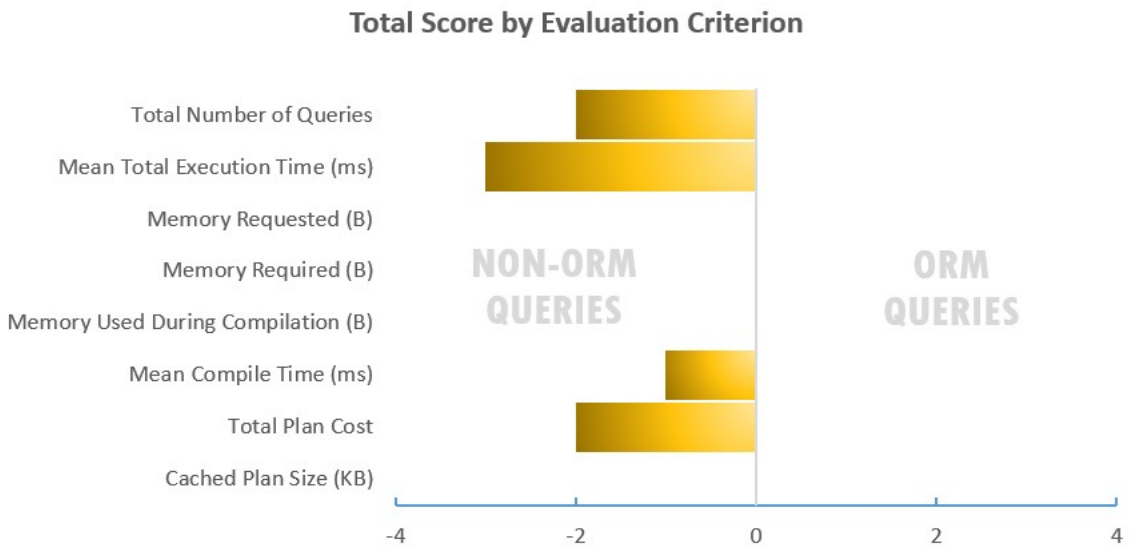
Discussion

The results are assessed against the evaluation criteria as follows. For each criterion, the two results – for the ORM-generated query, and for the non-ORM generated query – are compared using the condition for the criterion specified in the 'Comparative Rule' column (of Table 2). If the non-ORM result meets the condition, a score of -1 is assigned. If the ORM result meets the condition, a score of 1 is assigned. If the condition cannot be applied as both results are equal, 0 is assigned.

For illustration: For the criterion *Total Execution Time (ms)*, the comparative rule is *Shortest execution time*. The results obtained, as per Table 4, for this criterion across the 5 query objectives were as follows, in the format Non-ORM/ORM: 1482.0/1484.0, 537.6/596.4, 449.0/572.2, 1942.4/1829.8 and 98.0/32441.0. So for each pair, the smallest value is found, and the appropriate score assigned. Comparing each pair, we assign the scores as described: -1, -1, -1, 1, -1. Summing these scores yields -3. Consequently, the score for this criterion across all query objectives is -3.

In Figure 2, the scores for all 7 criteria are presented using this scoring mechanism. Negative scores are associated with non-ORM generated queries, positive scores with ORM-generated queries and zero scores with neither category. For every evaluation criterion, the results showed that non-ORM generated queries outperformed ORM-generated queries using the definitions of the respective comparative rules.

Figure 2. Total Score by Evaluation Criterion

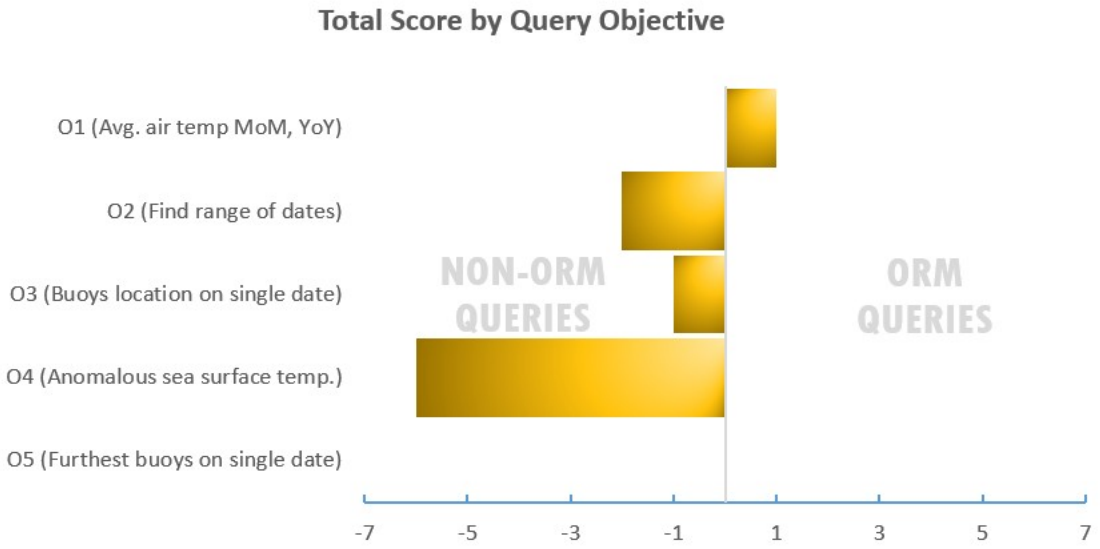


The data can also be presented pivoted by query objective (O1 to O5). For this analysis, the same scoring mechanism is used but instead of assessment solely by evaluation criterion, the assessment is by query objective, which helps illustrate the relationship between query complexity and superiority of method. The comparative rules of the evaluation criteria are used to assign scores, as before.

For illustration: For query objective O4, each pair of results is assessed against the respective comparative rules. The results are, in the format Non-ORM/ORM: 96/128, 5.24644/5.25825, 17.4/24.2, 776/856, 3712/5704, 3712/5704, 1942.4/1829.8 and 1/2. The comparative rules for each can be summarised as 'find the smallest value', and so for each pair the smallest value is found and the appropriate score assigned: -1, -1, -1, -1, -1, -1, 1, -1, which sums to -6. So the score for Objective O4 across all criteria is -6.

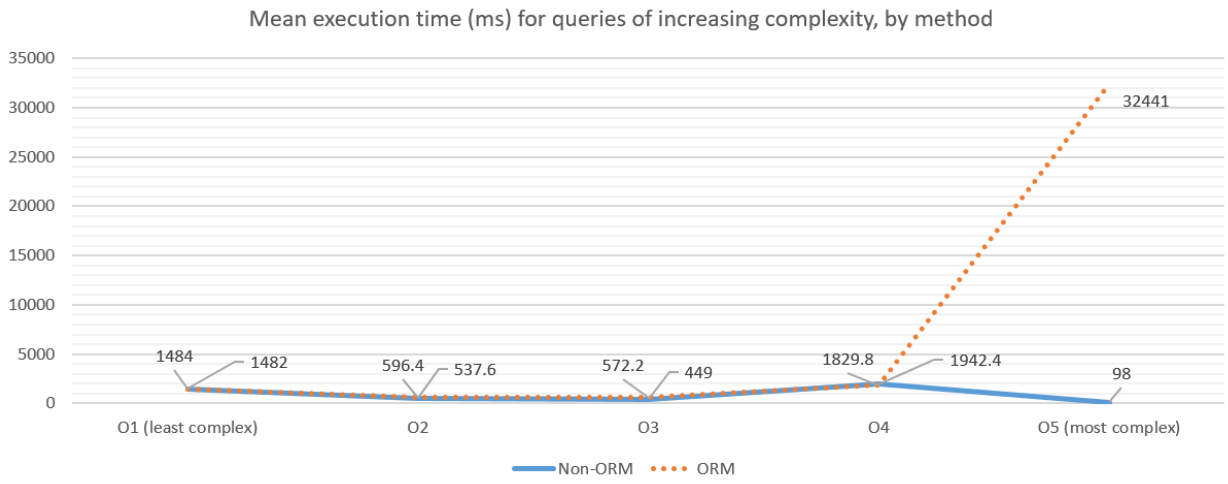
The scores for the query objectives across all evaluation criteria are illustrated in Figure 3. There is a correlation between query complexity and score – query objective O1, a simple query, had better overall performance when generated by an ORM than otherwise. Query objective O4, a complex query, had significantly better performance when generated by a non-ORM method than by the ORM, with only one evaluation criteria rating the ORM as better-performing.

Figure 3. Total Score by Query Objective



However, query objective O5 shows a neutral result despite the complexity of the query, and the reason is that the number of evaluation criteria that favoured non-ORM generated queries was equal to the number favouring ORM-generated queries, so no clear determination can be made. This highlights a weakness in this analysis approach –each criterion is given equal weighting in the scoring despite extremes in the data and comparative importance of each criterion. Query execution time can be thought of as a strong desirable trait in query performance outcomes, perhaps more so (from the user's perspective) than plan cost or memory use, and an equal weighting for all criteria obfuscates this view. This weakness can be overcome by drawing upon the data in detail. Figure 4 illustrates the relationship, drawn from the results between mean total execution time and query objectives, or complexity (where O1 is least complex and O5 most complex).

Figure 4. Correlation between increasing complexity and execution time of ORM methods.



This result shows that there is a generally positive correlation between complexity of query and the time taken to execute the query derived by the ORM-generated method, even if the result from O5 as an extreme outlier is excluded.

Performing t-testing on the observations of the mean execution time across the query objectives illustrated in Figure 2, this analysis is borne out by the *p*-values obtained for all the observations. Table 5 shows that in these t-tests, $p > 0.05$ (highlighted). This supports the conclusion that there is a significant uplift in the execution time of the ORM-generated queries than the non-ORM generated queries as complexity rises.

Table 5: p-values from t-testing of mean execution time observations

	Non-ORM	*ORM*
Mean	901.8	7384.68
Variance	600811.08	196496129.3
Observations	5	5
Hypothesized Mean Difference	0	
P(T<=t) one-tail	**0.180**	
P(T<=t) two-tail	**0.360**	

In general, the results showed that as query complexity rose, ORM-generated queries incurred performance penalties across multiple evaluation criteria, and started to exhibit performance anti-patterns referenced in the literature (Karwin, 2017; Chen et al., 2014) and observed in related studies (Colley, Stanier & Asaduzzaman, 2018; Colley & Stanier, 2017). *p*-value testing of the results of one important evaluation criterion helped support the evidence ($p > 0.05$) that this correlation exists.

The scope of the investigation was over a relatively small data set of three tables. The results, showing divergence across many of the performance measures between both ORM-generated queries and non-ORM generated queries, are likely to diverge further as the complexity of the database schema and the amount of data involved increases, a conclusion supported by the evidence from the survey detailing performance deficits in ORM tools from database practitioners.

CONCLUSION

The survey results were analysed thematically and a number of narratives drawn from the findings. These narratives were characterised as ORM use; education, awareness and perception; negative ORM behaviour; and future outlook. The survey results suggested that ORM tools are not ubiquitous but are present in a sizeable minority of respondents' organisations. It was felt that ORMs were fundamentally incompatible in several ways with RDBMS systems; that they were difficult to tune, and this was supported by examples from the respondents that were echoed in the literature. The findings suggested that at least some of the performance difficulties associated with ORM tooling can be attributed to lack of awareness in the developer community in how to use these tools efficiently, although this conclusion is arguably countered by the differences of opinion between the database administration community and the developer community (Ambler, 2018; Neward, 2006). The survey findings was supportive in general of

automation and positive about the future of relational database performance tuning, albeit sceptical of the role that ORM tooling may play in that future.

The exploration of the objectives was continued in the experimental investigation. Five query objectives were defined and based on a real data set were constructed and presented in increasing order of complexity, and the performance of ORM and non-ORM generated versions compared.

The outcome of the experimentation showed that when the results were grouped by performance metric, manually-written (non-ORM) queries outperformed ORM-generated queries. This meant that after assessing each query by each evaluation criterion and producing sum totals grouped by criterion in no cases did ORM queries outperform manually-written queries; this only occurred when considering individual results, and for low levels of complexity. The findings were then pivoted to analyse the evaluation criteria by the queries in increasing order of complexity. Using this view of the data it was shown that in 3 of 5 cases, manually-written queries outperformed ORM-generated queries, with 1 *vice versa* case and 1 inconclusive observation. Deconstructing the outcomes by query complexity, it was found there was a positive correlation between query complexity and query execution time and that the ORM-generated queries consistently took longer to run ($p = 0.18$) than non-ORM queries as complexity increased.

Additionally, undesirable behaviour was observed by the ORM tooling and mirrored some of the behaviour listed by the respondents of the survey and detailed in the literature. In particular, redundant code, lack of support for the full language, multiple queries, implicit conversion and row-by-row processing (the N+1 problem) were observed. It is noteworthy that another anti-pattern, eager fetching, could have been easily replicated through a choice to use an alternative function to *select_related* within the Python code calling the ORM, illustrating the ease in which these behaviours can be exhibited.

In summary, the survey findings and experimental evidence support the conclusion that ORM tooling has negative performance implications as query complexity increases, both in terms of material, measurable performance impacts to the calling application and system resources, and through the display of inefficient design patterns. These findings help to explain negativity observed in the survey findings on ORMs generally and their place in future database performance tuning technologies. ORMs are widespread but not universally used with the survey findings suggesting that barriers to adoption are related to perceived poor performance, and so there is a gap for future research into approaches to mitigate or remove the negative impacts to database query performance caused by ORM tools.

Future Work

This research has illustrated the need to consider alternative approaches to database performance tuning that are better able to assist in compiling and executing queries generated from non-traditional sources such as ORM frameworks. Such a solution could take the form of a flexible database performance management framework capable of handling sub-optimal queries.

One potential solution is a model incorporating some degree of schema selectivity. One of the issues noted in the findings of this paper was the existence of redundant code and the existence of implicit conversion problems. Other undesirable behaviours, such as fetching more columns than required, suggest that a potential direction is the creation of multiple schemas within a database, each of which is essentially a ‘whole-database’ index. Currently, indexes are created on tables or views, but conceptually there is no barrier to creating indexed views that encompass a large number of tables. Building alternative schemas on the same tree-based principles as indexes but widening the scope to multiple objects could form the basis of a new schema selection algorithm. Chen (1999) investigated the choice of alternate

schemata on a query-by-query basis with initially positive findings. One potential direction would be the employment of a query comparison and schema selection algorithm using an alternative model for query representation. The viability and detail of such a solution is a current research topic for the authors.

REFERENCES

Ambler, S. W. (2008). When it gets cultural: Data management and Agile development. *IT Professional* (vol. 10, issue 6, pp 11-14). IEEE. Retrieved from https://ieeexplore.ieee.org/abstract/document/4747648

Ambler, S. W. (2018). *The Cultural Impedance Mismatch Between Data Professionals and Application Developers*. Retrieved from http://www.agiledata.org/essays/culturalImpedanceMismatch.html

An, Y., Hu, X. & Song, I. (2010). Maintaining mappings between conceptual models and relational schemas. *Journal of Database Management* (vol. 21, issue 3, pp.36-). Retrieved from http://dx.doi.org.ezproxy.staffs.ac.uk/10.4018/jdm.2010070102

Aronson, J. (1995). A pragmatic view of thematic analysis. In *The Qualitative Report* (vol. 2, issue 1, pp.1-3). Retrieved from https://nsuworks.nova.edu/tqr/vol2/iss1/3/

Astrahan, M.M., Blasgen, M.W., Chamberlin, D.D., Eswaran, K.P., Gray, J.N., Griffiths, P.P., King, W.F., Lorie, R.A., McJones, P.R., Mehl, J.W. & Putzolu, G.R. (1976). System R: Relational approach to database management. In *ACM Transactions on Database Systems* (Vol 1., issue 2, pp.97-137).

Baroni, M., Dinu, G., & Kruszewski, G. (2014). Don't count, predict! A systematic comparison of context-counting vs. context-predicting semantic vectors. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)* (Vol. 1, pp. 238-247). Retrieved from http://clic.cimec.unitn.it/marco/publications/acl2014/baroni-etal-countpredict-acl2014.pdf

Bay, D.S., Kibler, D.F, Pazzani, M.J. & Smyth, P. (2000). The UCI KDD Archive of Large Data Sets for Data Mining Research and Experimentation. In *SIGKDD Explorations* (Vol. 2). Retrieved from https://www.ics.uci.edu/~pazzani/Publications/kdd_archive.pdf

Chen, C. M., & Roussopoulos, N. (1994). The implementation and performance evaluation of the ADMS query optimizer: Integrating query result caching and matching. In *International Conference on Extending Database Technology* (pp. 323-336). Berlin: Springer.

Chen, A. N. (1999). *Improving database performances in a changing environment with uncertain and dynamic information demand: An intelligent database system approach* (Doctoral dissertation). University of Connecticut. Retrieved from: https://opencommons.uconn.edu/dissertations/AAI9942566/

Chen, T., Shang, W., Jiang, Z.M., Hassan, A.E., Nasser, M. & Flora, P. (2014). Detecting performance anti-patterns for applications developed using object-relational mapping. In *Proceedings of the 36th International Conference on Software Engineering* (pp. 1001-1012).

Cheung, A., Madden, S. & Solar-Lezama, A. (2016). Sloth: Being lazy is a virtue (when issuing database queries). In *ACM Transactions on Database Systems* (vol. 41, issue 2, p.8).

Clarke, V. & Braun, V. (2013). Teaching thematic analysis: Overcoming challenges and developing strategies for effective learning. In *The Psychologist* (vol. 26, issue 2, pp. 120-123). Retrieved from http://eprints.uwe.ac.uk/21155

Codd, E. F. (1974). Recent Investigations into Relational Data Base Systems. *IBM Research Report RJ 1385*. Republished in *Proceedings of the 1974 Congress*. New York, NY: North-Holland.

Colley, D. & Stanier, C. (2017). Identifying New Directions in Database Performance Tuning. In *Procedia Computer Science* (vol. 121, pp. 260-265). Retrieved from https://www.sciencedirect.com/science/article/pii/S1877050917322275

Colley, D., Stanier, S. & Asaduzzaman, M. (2018). The Impact of Object-Relational Mapping Frameworks on Relational Query Performance. In *Proceedings of the International Conference on Computer, Electrical and Electronics Engineering 2018 (ICCECE '18)*. Advance online publication, DOI: 978-1-5386-4904-6/18. Retrieved from https://www.researchgate.net/profile/Derek_Colley/publication/328488840_The_Impact_of_Object-Relational_Mapping_Frameworks_on_Relational_Query_Performance/links/5bd09321a6fdcc6f79ff12b9/The-Impact-of-Object-Relational-Mapping-Frameworks-on-Relational-Query-Performance.pdf

Date, C. J. (1990). *Relational database writings, 1985-1989, volume 1*. Boston, MA: Addison-Wesley.

Fritchey, G. (2018). *SQL Server 2017 Query Performance Tuning* (Ch. 7). New York, NY: Apress.

He, Zhen. (2005). Evaluating the Dynamic Behavior of Database Applications. In *Journal of Database Management* (vol. 16, issue 2, pp. 21-45). Retrieved from http://dx.doi.org.ezproxy.staffs.ac.uk/10.4018/jdm.2005040102

Held, G.D., Stonebraker, M.R. & Wong, E. (1975). INGRES: a relational data base system. In *Proceedings of the May 19-22, 1975 National Computer Conference and Exposition* (pp. 409-416).

Ireland, C., Bowers, D., Newton, M. & Waugh, K. (2009). A Classification of Object-Relational Impedance Mismatch'. In *First International Conference on Advances in Databases, Knowledge, and Data Applications* (pp. 36-43). Retrieved from https://ieeexplore.ieee.org/abstract/document/5071809

Karwin, B. (2017). *SQL Antipatterns*. Rayleigh, NC: Pragmatic Bookshelf.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C. & Byers, A.H. (2011). *Big data: The next frontier for innovation, competition, and productivity.* McKinsey Global Institute. Retrieved from https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Digital/Our%20Insights/Big%20data%20The%20next%20frontier%20for%20innovation/MGI_big_data_exec_summary.ashx

Microsoft Corporation (2009). *Getting Started with Entity Framework 6 Code First using MVC 5*. Retrieved from https://docs.microsoft.com/en-us/aspnet/mvc/overview/gettingstarted/getting-started-with-ef-using-mvc/creating-an-entity-framework-data-model-for-an-asp-net-mvc-application

Neward, T. (2006). *The Vietnam of Computer Science.* Retrieved from https://pdfs.semanticscholar.org/331e/490c55ee72d6011bbceb323c03f0572a5235.pdf

Pachev, S. (2007). *Understanding MySQL Internals (Chapter 9: Parser and Optimiser)*. California: O'Reilly.

Pacific Marine Environmental Laboratory (PMEL), National Oceanic and Atmospheric Administration (NOAA) (2018). *El Nino Data Set*. Retrieved from https://archive.ics.uci.edu/ml/datasets/El+Nino

Niu, B., Martin, P. & Powley, W. (2009). Towards Autonomic Workload Management in DBMSs. *Journal of Database Management* (vol. 20, issue 3). Retrieved from https://www-igi-global-com.ezproxy.staffs.ac.uk/gateway/article/4122

Solid IT (2018). *DB-Engines Ranking*. Retrieved from https://dbengines.com/en/ranking

Spherical Trigonometry. (n.d.). In *Wikipedia*. Retrieved November 23, 2018, from https://en.wikipedia.org/wiki/Spherical_trigonometry

Stoll, R. R. (1963). *Set Theory and Logic*. USA: W H Freeman and Co.