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ANALYSE PROPERTY DATA THROUGH VISUALISATION

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ABSTRACT

People's activities create 2.5 quintillion bytes of data every day (Marr, 2018). The examples of activities include shopping, sleeping, property purchasing, selling or leasing, etc. A large amount of data is usually with high-dimensional geometry and multivariate characters. Traditional text-based data may be able to record the facts of activities, but the hidden story behind the data may not be discovered. Data visualisation is an instrument for reasoning about quantitative information and allows us to analyse data behaviours by understanding data patterns, trends and correlations that could not be detected by the traditional text-based data. This paper focuses on analysing property data for six suburbs in Sydney using visualisation. Data with 31 elements from the three-year censuses were used to create visual patterns for analysis. Parallel coordinates and dashboard techniques are applied for data visualization for the selected six suburbs. The results suggest that the well-designed data graphics is a powerful tool, and property data visualisation provides us with visual access to huge amounts of data in easily digestible visuals.

Keywords: *Property Data, Data Visualisation, Parallel Coordinates, Dashboard, Sydney*

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INTRODUCTION

The property market is a very complicated process that reflects an integration with various factors affecting demand for and supply of properties. The attitudes and behaviours of people are shaped by the complex, multi-dimensional and heterogeneity nature of property, i.e., peculiar characteristics such as location, size, and quality of construction, among others (Megbolugbe and Cho, 1993; Cruz and Morais, 2000), thus influence neighbourhood characteristics (Galaster, 1996). This implies that the property market is difficult to be described and analysed with challenge (Dawidowicz, et al., 2014) due to large amounts of data with high-dimensional geometry and multivariate characters. Marr (2018) suggested that people's activities create 2.5 quintillion bytes of data every day. Traditional text-based data may be able to record the facts of activities, but the hidden story behind the data may not be discovered. The questions of 'what visual method can be used to describe the data appropriately and assist with analysis of the pattern and correlations among the suburbs' should be asked.

Data visualisation is an instrument for reasoning about quantitative information, and allows us to analyse data behaviours by understanding data patterns, trends and correlations, that could not be detected by the traditional text-based data. Unwin, et al. (2008b) suggested that graphics provide an excellent approach for exploring data and are essential for presenting results. This paper focuses on analysing property data for six suburbs in Sydney using visualisation, in particular the application of parallel coordinates and dashboard in the property data visual analysis. The key contributions of this paper include three areas. Firstly, this paper explores a high-dimensional property data for visual analytics, against the traditions and commonly used of low-dimensional visualisation. Secondly, Parallel coordinates and dashboard technique are the first time introduced in the high-dimensional property data analytics. Thirdly, this paper fills up a gap in the body of knowledge in the visualising property data and the use of dashboard to display information as little literature addresses research areas previous.

Next section reviews briefly on the data visualisation techniques and applications. Data with 31 variables from the three-year censuses were used to create visual data for analysis. Parallel coordinates and dashboard techniques are applied for data visualization for the selected six suburbs. The results and conclusion will be discussed at the last.

REVIEW ON TYPES AND APPLICATIONS OF VISUALIZATION AND DASHBOARD

Data visualization uses technology to present concepts into charts and graphs manner. With interactive visualization, decision makers can look at the analytics presented visually to identify new patterns or discover difficult concepts and make data-backed or informed decisions. The benefits of presenting visual data are that data visualization is easier to visualize large amounts of complex data using charts or graphs that spreadsheets or reports; and a quick way to convey concepts and to meaningful results or communicate the insights derived from data analysis (French, 2018). Data visualization is not a new concept. It evolves from maps and diagrams in the 15^{th} century to the invention of the pie chart in the early 1800s, and then develops to high dimensional interactive and dynamic data visualisation from 1975 (Friendly, 2008). Figure 1 depicts the development of the data visualisation.

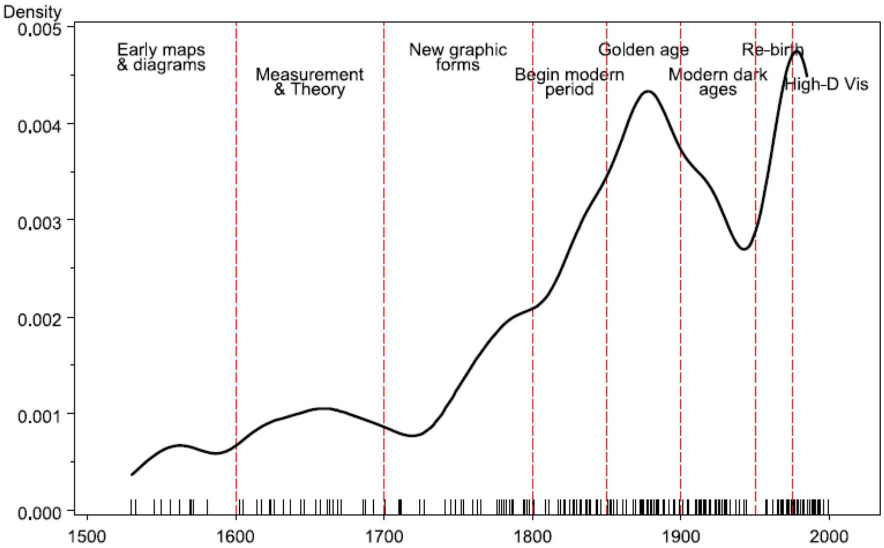

Figure 1. Milestones of visualisation: time course of developments (Source: Friendly, 2008, p.18)

Data can be classified as low or high dimensional types (i.e., 1-, 2-, 3-dimensional data, temporal and multi-dimensional data, and tree and network data) (Shneiderman, 1996). It becomes increasingly difficult to understand the information provided by the collected data when data dimensions are increased. The low dimensional data can be visualized using the line chart, bar chart, pie chart, geography map, scatter plot and tag cloud. However, with the low-dimensional data visualization, patterns that highlight multivariate relations cannot be revealed (Liu, et al., 2015). Thus, different aspects of high-dimensional data visualization such as parallel coordinates (Inselberg, 2009), visual data mining (Keim, 2002), clutter reduction (Ellis and Dix, 2007) were introduced.

Though data visualization has been used extensively in statistics for a long time (Unwin, et al., 2008a), they were applied to genetic network reconstruction (Shieh and Guo, 2008), medical images (Lu, 2008), financial applications such as bankruptcy analysis, online auctions, and insurance risk processes (Unwin, et al., 2008b; Jank, et al., 2008; Burnecki and Weron, 2008). Data visualization has also been applied into real estate and construction disciplines and more recently using GIS (Liu, et al., 2011; Li, et al., 2005; Clapp, et al. 1997, Du, 2004) and spatial techniques (Cohen and Coughlin, 2008; Case, et al., 2004; Gelfand, et al., 2004; Militino, et al., 2004; Dubin, et al., 1999). For example, how spatial techniques can be used to improve the accuracy of market value estimates obtained using multiple regression analysis was described by (Dubin, et al., 1999) who found the techniques can make a substantial improvement in predictive accuracy, change parameter estimates and their interpretation. However, the GIS software system is cumbersome, over-complicated, resource-hungry and require specialist expertise to understand and use (Smith, et al., 2007). The input data with GIS must be altered to generate a new output if alternative scenarios need to be tested (Chang, et al., 2007). Parallel coordinates technique (Heinrich and Weiskopt, 2013) has addressed this drawback to visual high-dimensional geometry and analysing multivariate data. The technique involves of transforming high dimensions geometry into 2D patterns, i.e., a set of points on a line in n-space transforms to a set of polylines in parallel coordinates all intersecting at $n-1$ points (Inselberg, 2009). This is to say that parallel coordinate visualization uses parallel axes to represent a data relationship, pattern and measurement for multi-dimensional data. The value of each axis can be numbers start from 0 to 9, or alphabet letter start from A to Z, or a to z. It enables to visualize any form of data into parallel coordinate.

For example, assume there are two data A and B, both have 3x dimensions (x, y, z) where

A (x=1, y=2, x=1) (1)

B (x=2, y=2, z=3) (2)

In the normal 3D graph, it will be illustrated as two points A and B. However, in parallel coordinate, it will be illustrated as two-line patterns of the relationship between axes X, Y, and Z (Figure 2).

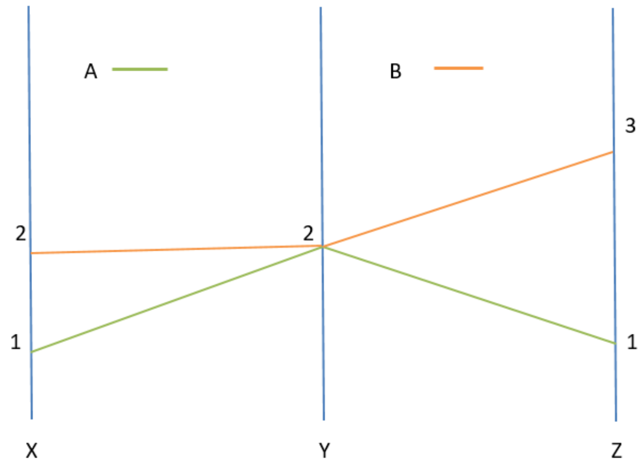

Figure 2. Parallel coordinates for A (x=1, y=2, z=1) and B (x=2, y=2, z=3)

Thus, for multidimensional data, parallel coordinate has a strong advantage in data visual analytics because it can be displayed all dimensional data in one chart (Inselberg, 2009).

Data overload is exacerbated nowadays, but human processing capacities remain limited (Simon, 1957; Pauwels, et al., 2009). Especially, the overloaded information could bias that have a great impact on decision making (Wierenga and Van Bruggen, 2000). A data dashboard is an information management tool that simplifies complex data sets to provide users with a visual display and at a glance awareness insights into the most important aspects of the data. In addition, a data dashboard can also display real-time key metrics and performance indicators to guiding decision making (Pauwels, et al., 2009). Low-dimensional visual techniques such as scatter plots, bar graphs and be used in a dashboard depends on the type of data collect, the way in which the data is manipulated and the how information can be best absorbed. The method of the dashboard is using excel function commands such as SUMPRODUCT, INDEX, and SUMIF. SUMPRODUCT. It is used to compare data in two or more ranges and calculating data with multiple criteria.

The functions of data visualization used in property analysis include a) identify information that need attention or improvement; b) clarify which factors influence households' behaviour; c) help to understand demographic profile; and d) predict trends or changes of demographic changes and property markets. The techniques of parallel coordinates and data dashboard visualisation can contribute to present multi-dimensional property data and market visually, so that analysis can be conducted, where low-dimensional graphs could not, for better investment and policy decision-making by stakeholders. An empirical study will be demonstrated in the next section.

EMPIRICAL STUDY

An empirical study is applied to demonstrate the use of parallel coordinates to visual high-dimensional geometry and analysing multivariate data. A table that used in an article by Ge (2018) is used to do the demonstration (Figure 3). The Figure records six categories of data including property price information, demographic and population, household financial status, dwelling types, unemployment and ethnic information of three census profile for six suburbs in Sydney. The dataset contains 6x suburbs with 31x elements for 3x years' data with a total of 558 data, which is a typical high-dimensional geometry data. From the table, it may be easy to find out the trend or changes of each variable in a particular suburb, for example, an increasing trend has been shown for 'owned by mortgage' in Parramatta. However, it might be difficult to identify which suburb had the highest 'owned by mortgage' in each of the census years at the given table. It is difficult to study the pattern of variables in a given year or a suburb and identify the relationships among the suburbs under the current table form.

Items	Parramatta			Westmead			Epping			Rhodes			Manly			Leichhardt		
	2001	2006	2011	2001	2006	2011	2001	2006	2011	2001	2006	2011	2001	2006	2011	2001	2006	2011
Transaction (House NO)	59	38	62	25	40	37	147	129	149	6	5	11	42	37	43	98	127	53
Median ('000)	$370	$460	$542.5	$383	$499	$615	$520	$705	$935	$408	$600	$1,030	$914.4	$1,300	$1,885	$451.5	$627	$820
Transaction (Unit NO)	393	217	770	85	126	319	105	80	220	3	84	604	199	188	363	37	83	81
Median ('000)	$230.0	$495.0	$425.0	$255.0	$302.5	$379.0	$329.0	$416.5	$580.5	$405.5	$504.9	$600.0	$465.0	$642.5	$695.0	$399.0	$408.8	$694.5
Median household weekly income	$900	$1,022	$1,314	$900	$1,064	$1,475	$1,100	$1,432	$1,683	$1,100	$1,565	$1,617	$1,100	$1,591	$2,084	$1,100	$1,516	$1,924
Median mortgage payment/month	$1,100	$1,571	$1,950	$1,100	$1,649	$2,000	$1,500	$1,950	$2,286	$1,500	$2,383	$2,600	$1,700	$2,300	$3,000	$1,500	$2,200	$2,817
Median weekly rent	$225	$230	$350	$225	$230	$360	$550	$300	$420	$275	$375	$560	$325	$380	$530	$325	$340	$460
Population	18292	18447	19745	10210	9486	14171	18347	18969	20227	743	1671	5679	14922	13949	15072	12608	12249	13520
Birthplace in Australia	6631	5991	5427	4542	3364	4271	10870	10174	10020	500	778	1349	7800	7207	7137	7995	7805	8791
Birthplace in Overseas	9157	10633	14318	4512	5368	9030	6567	7840	9595	181	646	3711	4497	4806	5818	3744	3430	4002
Birth (India)	1112	2603	4241	586	1543	4203	414	689	921	0	20	218	49	45	60	59	56	94
Birth (PR China)	1711	2370	2909	411	557	814	821	1559	2360	25	79	1441	77	85	77	60	67	106
Birth (UK)	392	309	235	256	171	197	681	597	560	36	61	125	1592	1750	2136	709	691	836
Birth (New Zealand)	469	403	326	231	195	220	264	243	225	8	26	92	671	612	626	412	380	433
Birth (Italy)	60	49	50	49	34	39	109	91	84	11	16	18	53	60	78	683	531	507
Australian citizen	11716	11111	10546	7088	6190	8589	15140	15237	16179	620	1130	2514	9708	8963	10055	10467	10028	11275
Median age	32	30	30	33	33	31	36	37	38	39	32	28	35	35	35	34	35	36
Fully owned	1378	976	870	698	511	606	3328	2724	2819	115	115	287	1875	1562	1550	1597	1191	1243
Owned with mortgage	930	1444	1685	372	688	1138	1235	1826	2084	56	192	627	740	978	1297	1308	1657	1907
Rented	4018	4361	4389	1978	2007	3018	1685	1784	2044	69	270	1210	3020	2797	3285	2191	2046	2165
Separate house (persons)	4148	3491	3023	2699	2722	2958	12999	13092	13414	504	475	538	2224	2586	2777	6217	5176	5712
Semi-detached (persons)	1699	2038	1232	347	363	1597	1247	1363	1807	159	198	253	1601	1441	1774	3780	4177	4337
Flat, unit, apartment (persons)	11153	11213	12916	4299	5329	8279	3733	3668	4315	13	723	4150	8874	7292	8513	1988	1750	2237
Total private dwellings (persons)	17208	16919	17225	8269	8418	12851	18041	18184	19577	676	1396	5000	12994	11391	13132	12199	11180	12392
Separate house (dwellings)	1444	1196	993	977	938	966	4300	4236	4447	168	160	198	793	940	985	2536	2109	2224
Semi-detached (dwellings)	711	759	461	151	149	614	500	522	661	78	91	103	695	581	704	1732	1830	1880
Flat, unit, apartment (dwellings)	5109	5008	5645	2155	2251	3319	1868	1711	1980	6	330	1838	5010	4004	4597	1178	1056	1293
Total private dwellings (dwellings)	8003	7073	7701	3693	3338	5223	7118	6521	7517	263	581	2462	7747	5577	7536	5905	5035	5884
Other dwellings	739	110	602	410	0	324	450	52	429	11	0	323	1249	52	1250	459	40	487
Unemployment(%)	9.5	8.1	8.2	8.8	8.3	7.5	4.6	4.3	6.1	4.9	6.3	7.8	4.6	3.3	3.7	.4.4	3.2	4.0
Average household size	2.4	2.4	2.4	2.4	2.5	2.6	2.7	2.8	2.8	2.7	2.4	2.3	2	2.1	2.1	2.2	2.2	2.3

Figure 3. Six suburb profiles of census data in Sydney (Source: Ge, 2018)

Data visualization technique, such as parallel coordinates, can address the drawbacks of the tabular form data presented in Figure 3 and visual high-dimensional geometry data. To illustrate the benefits of the parallel coordinates technique, we could include all 31x axes, however, there are 12x axes selected to represent parallel coordinates technique for visualising multiple dimensional data in this paper. The 12x axes includes census year, suburb's name, median house price, median unit price, fully owned percentage, unemployment rate, weekly income, ratio of birth in Australia, mortgage weekly payment, owned with mortgage, weekly rent price, and rented ratio. The basic parallel coordinates are created using Oracle data visualizer software (Oracle). Three steps are included to create the parallel coordinates visualisation. Firstly the collected table data are uploaded to the Oracle. Secondly, parallel axes are selected. The number of parallel axes selected are not restricted, which is one of the strengths of parallel coordinates visualisation. In this demonstration, total 12x axes have been selected including six locations and three census years. To generate parallel coordinates is the third step, which is shown in Figure 4. As a result, created parallel coordinates are able to put 12x dimensional data together to one chart and the relationships between each of the variables (axes) can be found. Three main findings could be summarised from the visual parallel coordinates.

First, when the year 2011 is selected on year's axis, 2011 property data patterns of six suburbs (Figure 4) and the where the colours are used to separate different suburbs. Parramatta have lowest full-owned property, following by Westmead and Rhodes in 2011. Rhode has lowest population birth in Australia, following by Parramatta and Westmead. Manly has highest median house price, median unit price, weekly income, and mortgage payment. Leichhardt has the highest ratio of owner with a mortgage, and Rhode has a highest weekly rent price.

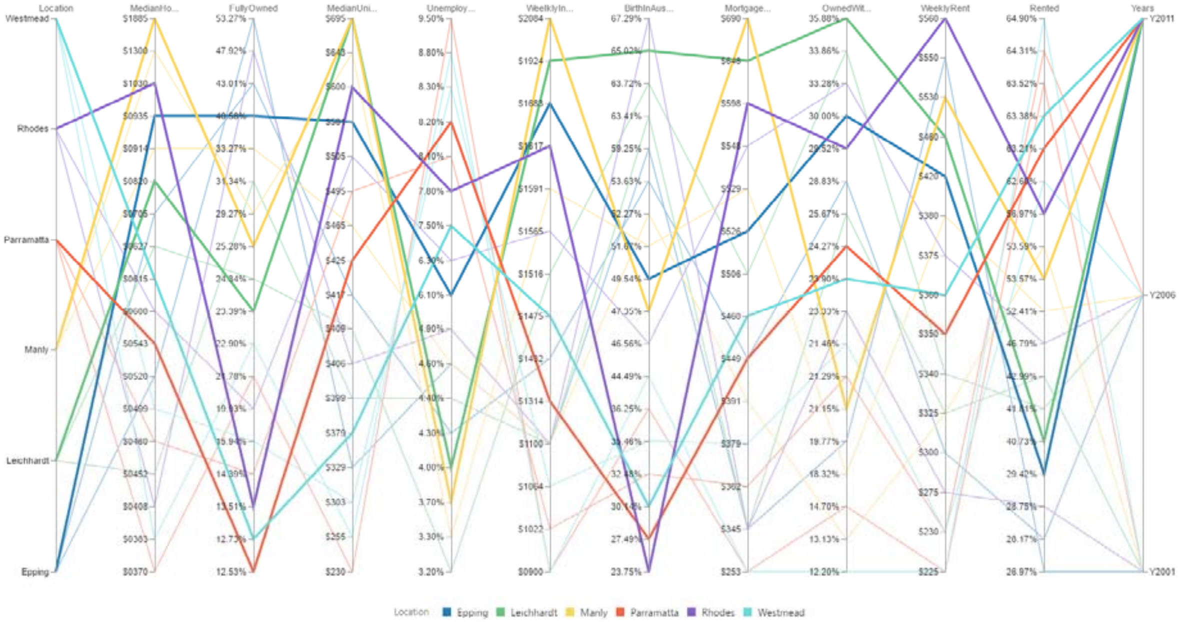

Figure 4. Selected view of property data parallel coordinate for 2011 (source: Authors)

Second, when the selection focuses on suburb's axis, for example, Rhodes has highest and lowest ratio of birth in Australia compares other 5 suburbs. In 2001, the population of Australia born is 67.29%. In 10 years' time, it dropped to 23.75% in 2011. And Rhodes has also biggest movement between 2001 and 2011 for median house price, property full ownership, mortgage weekly payment, and weekly rental price. In 2001, Rhodes is the bottom 3rd of median house price, top 2nd for property full ownership, bottom 2nd for mortgage weekly payment, and bottom 3rd for weekly rental price. However, in 2011 ten years later, median house price has raised to top 3rd, property full ownership dropped to bottom 3rd, mortgage weekly payment raised to top 3rd, and weekly rent price raided to top 1st (Figure 5).

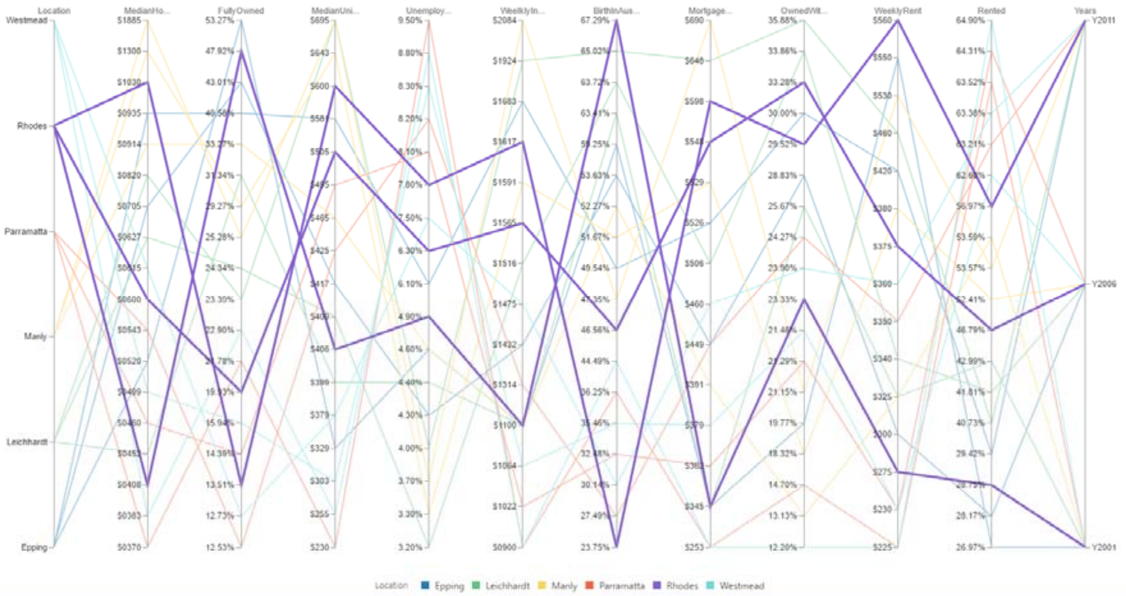

Figure 5. Selected view of property data parallel coordinate for Rhodes (Source: Authors)

Thirdly, the parallel coordinates can be used for attributes exploration. We can select multiple attributes from different axes to find out which pattern matching multiple criteria. Figure 6 shows the selection for both weekly income's axis and weekly rent price axis. In this Figure, we select an income range between $1200 and $1500 per week on weekly income axis, and then select rent price between $350 and $450 on weekly rent price axis. It is found that only two patterns matched our selection, i.e., suburb Parramatta and Rhodes in 2011. It is interesting to find out that those families who have income between $1200 - $1500 and pay rent between S350 -

$450 for their lives in 2011. Only two suburbs have suited this criteria, Parramatta and Rhodes. By using this technique, the feature of house affordability can be analysed.

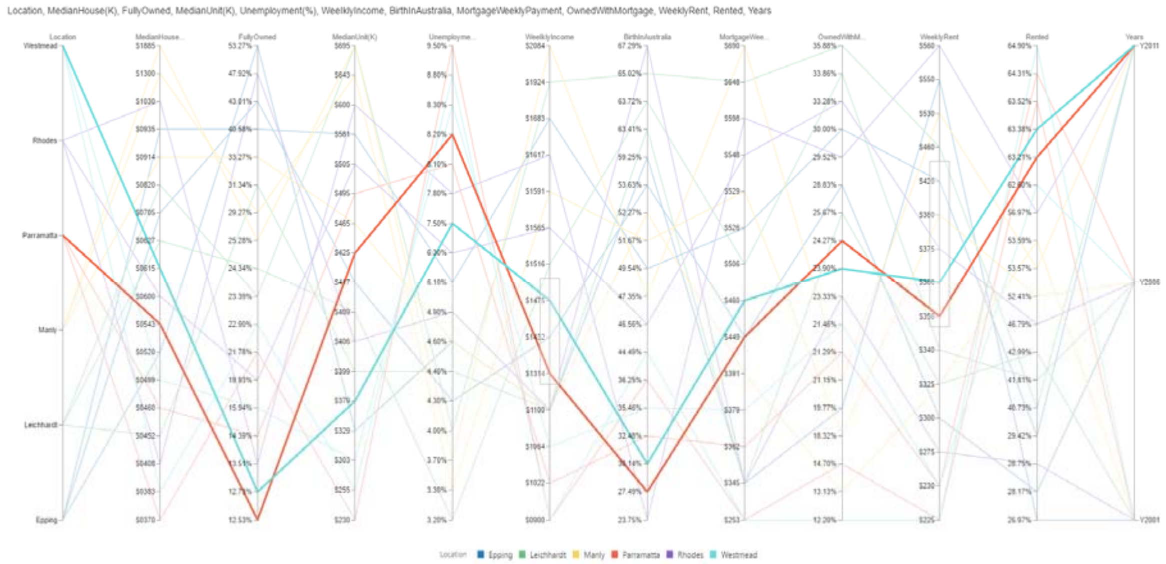

Figure 6. Select view for both weekly income's axis and weekly rent price axis (source: Authors)

While the technique of parallel coordinates offers a flexible visualisation to analyse multi-dimensional variables, data visualisation dashboards provides an overview of the profile by suburb and/or by year changes. To demonstrate, there are 5x dimensional data selected in the dataset including: property median price and transaction details; household finance status; population and ethnic information; dwelling information; employment and family status. To visualize those 31x elements (refer to Figure 3) and find out the trend and pattern, we grouped those five dimensional data into two parts: first part has demonstrated graphs in suburb's serials, and the second part is setting as time series charts. There are 10x visual graphs and 5x tables illustrated in this dashboard in total.

Suburb's serials visualization

In this visualization area, 4x visual graphs and 3x tables are illustrated which time serials have indicated. The market performances can be summarized in the dashboard (refer to Figure 7).

a) Yearly property median price trend and transaction information

   Yearly median price is based on transaction of properties. We used a line chart to illustrate suburb's median price and transaction statues which are best for comparing. Median house price is normally greater than the unit price except Parramatta. In 2006, the Parramatta median unit price was $495,000, greater than house median price which was $460,000.

b) Property ownership status

   We calculate three property ownership status: fully owned, owned by mortgage, and rented for visual analytics. Stacked bar chart has been used here to summarize the total property owned for suburb's ownership comparison. Rhodes's ownership has increased near 10 times from 2001 to 2011.

c) Household financial status

   We used three elements to measure the household financial status, there are median household weekly income, median mortgage weekly payment, and median weekly rent. The combo charts, bar charts and the mortgage line charts have been used here. The bar chart scaled the three facts, and line chart measured ratio for mortgage payment versus income and rent versus income. The ration of mortgage versus income is normally greater than rent versus income, however, in Epping at 2001, the ratio of rent versus income is 50% which is much higher than the mortgage versus income at 31%. Compare ownership chart, we find out the full ownership in Epping at the same year is much higher than others. It caused the rent price higher than a mortgage payment.

d) Number of persons owned property

   Three owned property status is categorised, i.e., separate house, semi-detached, and flat / unit / apartment. The combo chart, stacked bar chart and line chart have been used here. Stacked bar chart summarizes the total persons owned property for three status, and line chart displays the total private dwellings. Rhode has the biggest jump on persons owned property for the flat / unit / apartment in 2011. It explained why the property ownership status has increased nearly 10 times in Rhodes.

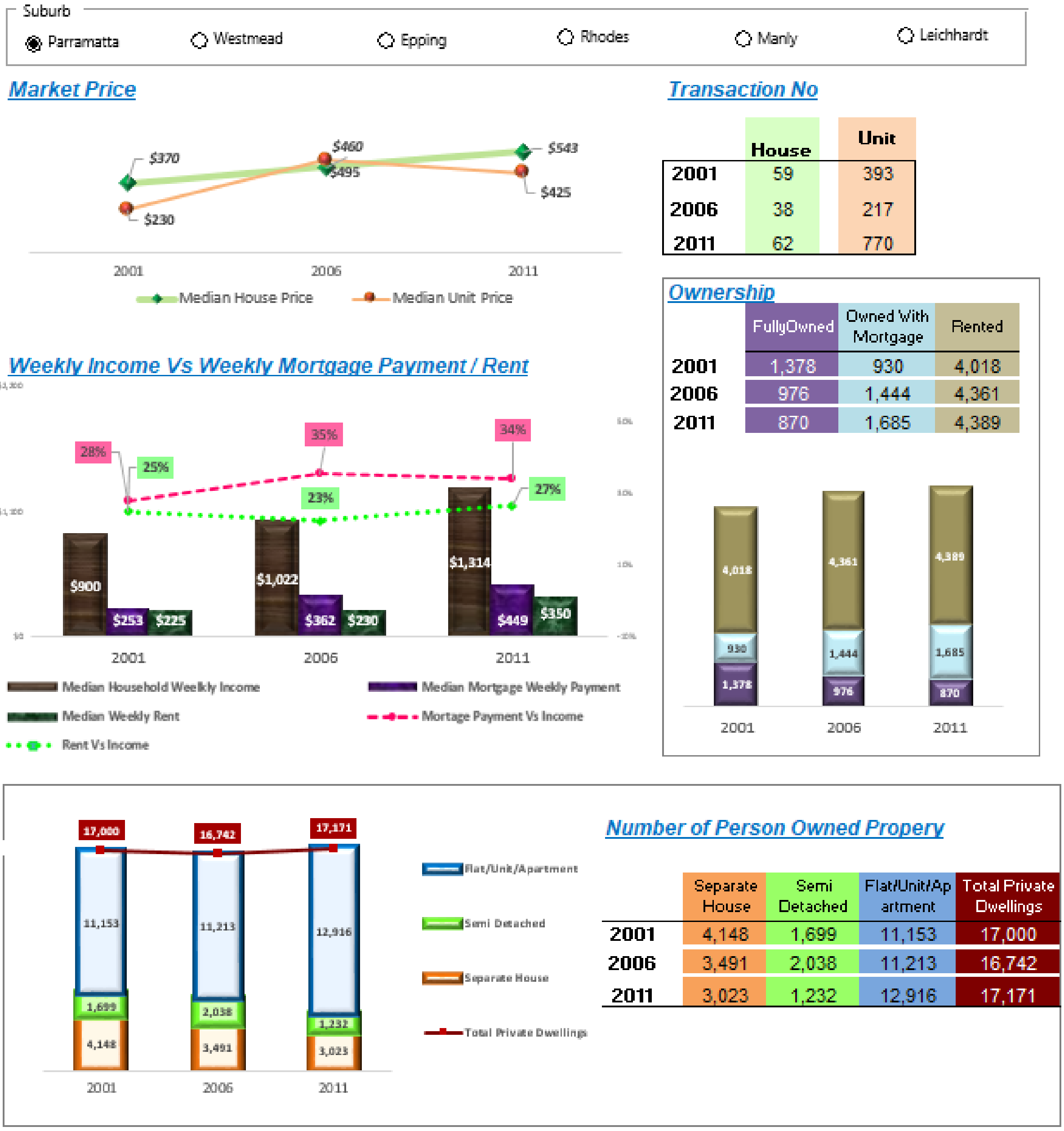

Figure 7. A dashboard of suburb profile by Suburb serials (source: Authors)

Time serials visualization

In this visualization area, 6x visual graphs and 2x tables are illustrated, which firstly based on suburb's serials selection, and then separated by time series between 2001 and 2011. Some points can be drawn from the dashboard created (refer to Figure 8).

a) Median age, average household size, and unemployment

   Numbers and bar chart have been used here due to those three measurements are moving in small scales. It is shown that the median age in Rhodes's had dropped from 39 to 29 between 2001 and 2011, at the same time, average household size had also dropped from 2.7 to 2.3.

b) Population and ethnic information

   We use two areas to visualize the population and ethnic information. The first area uses pie chart and bubble chart to illustrate the total population and its details. The second area has compared birth place in overseas, which illustrated top five birth countries. The table next to pie chart has displayed those details. In

Parramatta and Westmead, the India born population had added more than 6500 persons between 2001 and 2011. It was about 20% increased. In Manly UK born population had increased 4%, in Epping China born population had increased 6.8%, and however, there was not much change in Leichhardt. In Rhodes, total population had jumped from 743 in 2001 to 5,679 in 2011. During these ten years, China born population had increased from 3.4% to 25.4%.

c) Australian citizen status
We use stacked line chart to demonstrate Australian population crossing six suburbs. The stacked line chart has no crossed lines that have clearly illustrated percentage of Australian citizens. The blue line represents 2001, red line for 2006 and green line for 2011.

d) Private dwellings information
We use two charts to illustrate private dwelling information. The first chart uses line chart which demonstrates total private dwelling by suburb. The second chart is 3D pie chart which illustrates the percentage of four private dwelling status: separate house, semi-detached house, flat/unit/apartment, and other dwellings. In Rhodes, the detached house had dropped from 64% to 6% between 2001 and 2011, and the flat/unit/apartment had increased from 2% to 75% in the same period. A table contains the details of that private dwelling information.

The empirical study presented above has demonstrated that the property data visualization dashboard clearly visualized all property information in one screen. Ten visual graphs and five tables have been illustrated in this dashboard. Clickable selection for suburb's serials and time's serials enabled data-alive screen which provides data movement in real-time. Suburb's profile comparison, property price trend discovery, property storytelling, all those property economic data analytics can be done in this dashboard.

CONCLUSION

The exploration the use of Parallel coordinates and data dashboard techniques in property data research is an innovation in this paper. The study has drawn on the limitations of previous low-dimensional visual graph to demonstrate how the parallel coordinate technique is used to visualise high-dimensional data and improve the analysed ability. The application of the dashboard has also illustrated for the use of real-time analysis. The empirical results align with the previous findings (Inselberg, 2009) that parallel coordinate has a strong advantage in data visual analytics because it can be displayed all dimensional data in one chart. In addition, a data dashboard can also display real-time key metrics and performance indicators to address the overloaded information (Pauwels, et al., 2009). Thus, same conclusion can be drawn from the study includes that, firstly low-dimensional graphs are not appropriately used for the multi-dimensional and variety data due to some and important of a data feature could be lost in the low-dimensional graphs. Second, the main power of parallel coordinates is that it can include multi-dimensional data into one graph and the data feature, trend, relationships amount the data can be viewed and thus analysed. The empirical results also support that the well-designed data graphics is a powerful tool, and property data visualisation provides us visual access to huge amounts of data in easily digestible visuals.

This paper provides a preliminary study of the data visualisation for multi-dimensional data using parallel coordinates and dashboards and the first application in the real estate data analysis. There are many applications of the techniques including the housing affordability study and price forecasting that can be explored further. In addition, how use friendly parallel coordinates and dashboard design to improve the visualisation are other areas for further study.

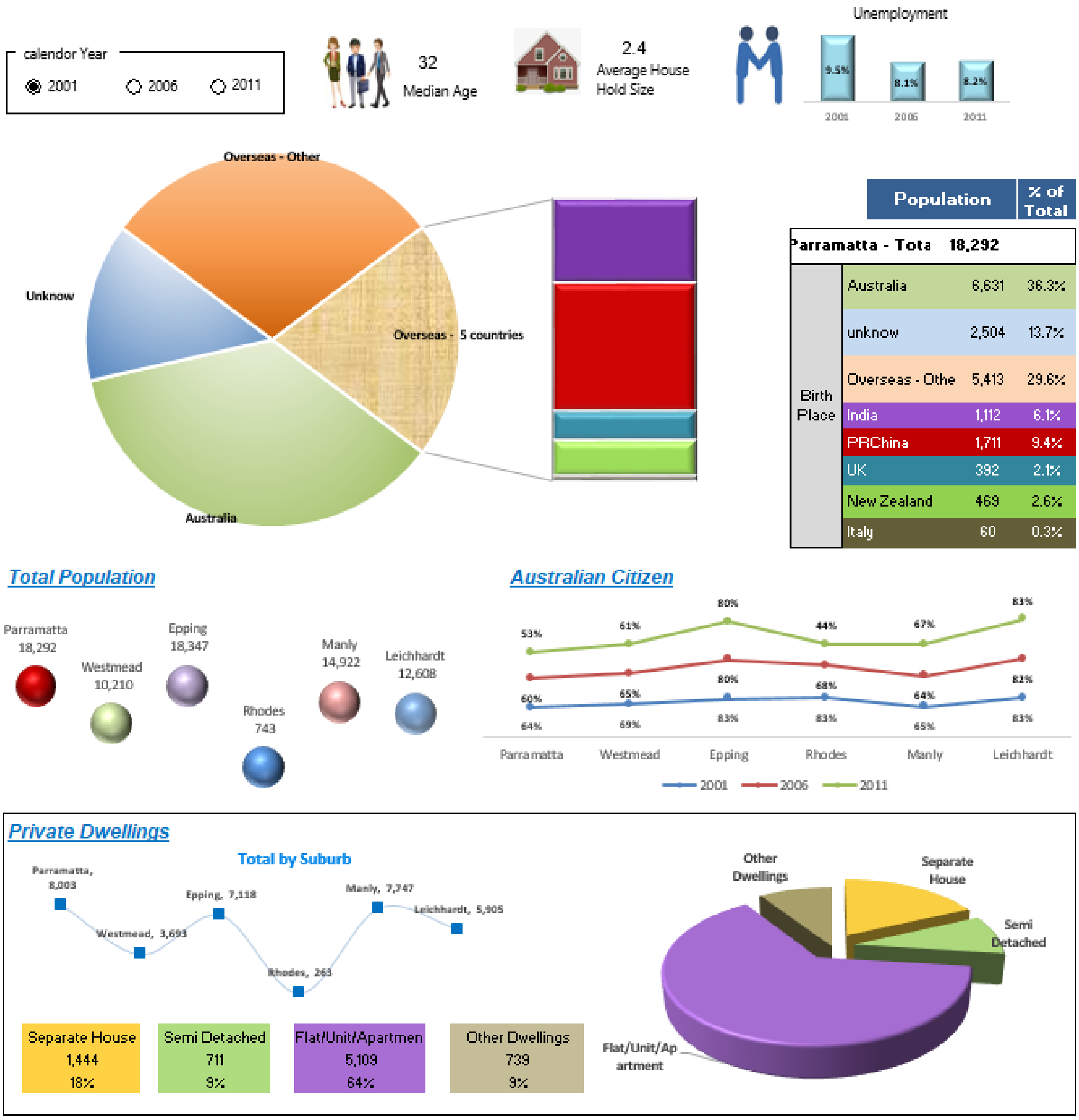

Figure 8. A dashboard of suburb profile by Time serials (source: Authors)

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