

TimeSeriesII.R

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Q. Build a timeSeries object with the data.

```
data("sunspots")  
sunspots
```

##	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
## 1749	58.0	62.6	70.0	55.7	85.0	83.5	94.8	66.3	75.9	75.5	158.6
## 1750	73.3	75.9	89.2	88.3	90.0	100.0	85.4	103.0	91.2	65.7	63.3
## 1751	70.0	43.5	45.3	56.4	60.7	50.7	66.3	59.8	23.5	23.2	28.5
## 1752	35.0	50.0	71.0	59.3	59.7	39.6	78.4	29.3	27.1	46.6	37.6
## 1753	44.0	32.0	45.7	38.0	36.0	31.7	22.2	39.0	28.0	25.0	20.0
## 1754	0.0	3.0	1.7	13.7	20.7	26.7	18.8	12.3	8.2	24.1	13.2
## 1755	10.2	11.2	6.8	6.5	0.0	0.0	8.6	3.2	17.8	23.7	6.8
## 1756	12.5	7.1	5.4	9.4	12.5	12.9	3.6	6.4	11.8	14.3	17.0
## 1757	14.1	21.2	26.2	30.0	38.1	12.8	25.0	51.3	39.7	32.5	64.7
## 1758	37.6	52.0	49.0	72.3	46.4	45.0	44.0	38.7	62.5	37.7	43.0
## 1759	48.3	44.0	46.8	47.0	49.0	50.0	51.0	71.3	77.2	59.7	46.3
## 1760	67.3	59.5	74.7	58.3	72.0	48.3	66.0	75.6	61.3	50.6	59.7
## 1761	70.0	91.0	80.7	71.7	107.2	99.3	94.1	91.1	100.7	88.7	89.7
## 1762	43.8	72.8	45.7	60.2	39.9	77.1	33.8	67.7	68.5	69.3	77.8
## 1763	56.5	31.9	34.2	32.9	32.7	35.8	54.2	26.5	68.1	46.3	60.9
## 1764	59.7	59.7	40.2	34.4	44.3	30.0	30.0	30.0	28.2	28.0	26.0
## 1765	24.0	26.0	25.0	22.0	20.2	20.0	27.0	29.7	16.0	14.0	14.0
## 1766	12.0	11.0	36.6	6.0	26.8	3.0	3.3	4.0	4.3	5.0	5.7
## 1767	27.4	30.0	43.0	32.9	29.8	33.3	21.9	40.8	42.7	44.1	54.7
## 1768	53.5	66.1	46.3	42.7	77.7	77.4	52.6	66.8	74.8	77.8	90.6
## 1769	73.9	64.2	64.3	96.7	73.6	94.4	118.6	120.3	148.8	158.2	148.1
## 1770	104.0	142.5	80.1	51.0	70.1	83.3	109.8	126.3	104.4	103.6	132.2
## 1771	36.0	46.2	46.7	64.9	152.7	119.5	67.7	58.5	101.4	90.0	99.7
## 1772	100.9	90.8	31.1	92.2	38.0	57.0	77.3	56.2	50.5	78.6	61.3
## 1773	54.6	29.0	51.2	32.9	41.1	28.4	27.7	12.7	29.3	26.3	40.9
## 1774	46.8	65.4	55.7	43.8	51.3	28.5	17.5	6.6	7.9	14.0	17.7
## 1775	4.4	0.0	11.6	11.2	3.9	12.3	1.0	7.9	3.2	5.6	15.1
## 1776	21.7	11.6	6.3	21.8	11.2	19.0	1.0	24.2	16.0	30.0	35.0
## 1777	45.0	36.5	39.0	95.5	80.3	80.7	95.0	112.0	116.2	106.5	146.0
## 1778	177.3	109.3	134.0	145.0	238.9	171.6	153.0	140.0	171.7	156.3	150.3
## 1779	114.7	165.7	118.0	145.0	140.0	113.7	143.0	112.0	111.0	124.0	114.0
## 1780	70.0	98.0	98.0	95.0	107.2	88.0	86.0	86.0	93.7	77.0	60.0
## 1781	98.7	74.7	53.0	68.3	104.7	97.7	73.5	66.0	51.0	27.3	67.0
## 1782	54.0	37.5	37.0	41.0	54.3	38.0	37.0	44.0	34.0	23.2	31.5

## 1783	28.0	38.7	26.7	28.3	23.0	25.2	32.2	20.0	18.0	8.0	15.0
## 1784	13.0	8.0	11.0	10.0	6.0	9.0	6.0	10.0	10.0	8.0	17.0
## 1785	6.5	8.0	9.0	15.7	20.7	26.3	36.3	20.0	32.0	47.2	40.2
## 1786	37.2	47.6	47.7	85.4	92.3	59.0	83.0	89.7	111.5	112.3	116.0
## 1787	134.7	106.0	87.4	127.2	134.8	99.2	128.0	137.2	157.3	157.0	141.5
## 1788	138.0	129.2	143.3	108.5	113.0	154.2	141.5	136.0	141.0	142.0	94.7
## 1789	114.0	125.3	120.0	123.3	123.5	120.0	117.0	103.0	112.0	89.7	134.0
## 1790	103.0	127.5	96.3	94.0	93.0	91.0	69.3	87.0	77.3	84.3	82.0
## 1791	72.7	62.0	74.0	77.2	73.7	64.2	71.0	43.0	66.5	61.7	67.0
## 1792	58.0	64.0	63.0	75.7	62.0	61.0	45.8	60.0	59.0	59.0	57.0
## 1793	56.0	55.0	55.5	53.0	52.3	51.0	50.0	29.3	24.0	47.0	44.0
## 1794	45.0	44.0	38.0	28.4	55.7	41.5	41.0	40.0	11.1	28.5	67.4
## 1795	21.4	39.9	12.6	18.6	31.0	17.1	12.9	25.7	13.5	19.5	25.0
## 1796	22.0	23.8	15.7	31.7	21.0	6.7	26.9	1.5	18.4	11.0	8.4
## 1797	14.4	4.2	4.0	4.0	7.3	11.1	4.3	6.0	5.7	6.9	5.8
## 1798	2.0	4.0	12.4	1.1	0.0	0.0	0.0	3.0	2.4	1.5	12.5
## 1799	1.6	12.6	21.7	8.4	8.2	10.6	2.1	0.0	0.0	4.6	2.7
## 1800	6.9	9.3	13.9	0.0	5.0	23.7	21.0	19.5	11.5	12.3	10.5
## 1801	27.0	29.0	30.0	31.0	32.0	31.2	35.0	38.7	33.5	32.6	39.8
## 1802	47.8	47.0	40.8	42.0	44.0	46.0	48.0	50.0	51.8	38.5	34.5
## 1803	50.0	50.8	29.5	25.0	44.3	36.0	48.3	34.1	45.3	54.3	51.0
## 1804	45.3	48.3	48.0	50.6	33.4	34.8	29.8	43.1	53.0	62.3	61.0
## 1805	61.0	44.1	51.4	37.5	39.0	40.5	37.6	42.7	44.4	29.4	41.0
## 1806	39.0	29.6	32.7	27.7	26.4	25.6	30.0	26.3	24.0	27.0	25.0
## 1807	12.0	12.2	9.6	23.8	10.0	12.0	12.7	12.0	5.7	8.0	2.6
## 1808	0.0	4.5	0.0	12.3	13.5	13.5	6.7	8.0	11.7	4.7	10.5
## 1809	7.2	9.2	0.9	2.5	2.0	7.7	0.3	0.2	0.4	0.0	0.0
## 1810	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
## 1811	0.0	0.0	0.0	0.0	0.0	0.0	6.6	0.0	2.4	6.1	0.8
## 1812	11.3	1.9	0.7	0.0	1.0	1.3	0.5	15.6	5.2	3.9	7.9
## 1813	0.0	10.3	1.9	16.6	5.5	11.2	18.3	8.4	15.3	27.8	16.7
## 1814	22.2	12.0	5.7	23.8	5.8	14.9	18.5	2.3	8.1	19.3	14.5
## 1815	19.2	32.2	26.2	31.6	9.8	55.9	35.5	47.2	31.5	33.5	37.2
## 1816	26.3	68.8	73.7	58.8	44.3	43.6	38.8	23.2	47.8	56.4	38.1
## 1817	36.4	57.9	96.2	26.4	21.2	40.0	50.0	45.0	36.7	25.6	28.9
## 1818	34.9	22.4	25.4	34.5	53.1	36.4	28.0	31.5	26.1	31.7	10.9
## 1819	32.5	20.7	3.7	20.2	19.6	35.0	31.4	26.1	14.9	27.5	25.1
## 1820	19.2	26.6	4.5	19.4	29.3	10.8	20.6	25.9	5.2	9.0	7.9
## 1821	21.5	4.3	5.7	9.2	1.7	1.8	2.5	4.8	4.4	18.8	4.4
## 1822	0.0	0.9	16.1	13.5	1.5	5.6	7.9	2.1	0.0	0.4	0.0
## 1823	0.0	0.0	0.6	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.0
## 1824	21.6	10.8	0.0	19.4	2.8	0.0	0.0	1.4	20.5	25.2	0.0
## 1825	5.0	15.5	22.4	3.8	15.4	15.4	30.9	25.4	15.7	15.6	11.7
## 1826	17.7	18.2	36.7	24.0	32.4	37.1	52.5	39.6	18.9	50.6	39.5
## 1827	34.6	47.4	57.8	46.0	56.3	56.7	42.9	53.7	49.6	57.2	48.2
## 1828	52.8	64.4	65.0	61.1	89.1	98.0	54.3	76.4	50.4	54.7	57.0
## 1829	43.0	49.4	72.3	95.0	67.5	73.9	90.8	78.3	52.8	57.2	67.6
## 1830	52.2	72.1	84.6	107.1	66.3	65.1	43.9	50.7	62.1	84.4	81.2
## 1831	47.5	50.1	93.4	54.6	38.1	33.4	45.2	54.9	37.9	46.2	43.5
## 1832	30.9	55.5	55.1	26.9	41.3	26.7	13.9	8.9	8.2	21.1	14.3

## 1833	11.3	14.9	11.8	2.8	12.9	1.0	7.0	5.7	11.6	7.5	5.9
## 1834	4.9	18.1	3.9	1.4	8.8	7.8	8.7	4.0	11.5	24.8	30.5
## 1835	7.5	24.5	19.7	61.5	43.6	33.2	59.8	59.0	100.8	95.2	100.0
## 1836	88.6	107.6	98.1	142.9	111.4	124.7	116.7	107.8	95.1	137.4	120.9
## 1837	188.0	175.6	134.6	138.2	111.3	158.0	162.8	134.0	96.3	123.7	107.0
## 1838	144.9	84.8	140.8	126.6	137.6	94.5	108.2	78.8	73.6	90.8	77.4
## 1839	107.6	102.5	77.7	61.8	53.8	54.6	84.7	131.2	132.7	90.8	68.8
## 1840	81.2	87.7	55.5	65.9	69.2	48.5	60.7	57.8	74.0	49.8	54.3
## 1841	24.0	29.9	29.7	42.6	67.4	55.7	30.8	39.3	35.1	28.5	19.8
## 1842	20.4	22.1	21.7	26.9	24.9	20.5	12.6	26.5	18.5	38.1	40.5
## 1843	13.3	3.5	8.3	8.8	21.1	10.5	9.5	11.8	4.2	5.3	19.1
## 1844	9.4	14.7	13.6	20.8	12.0	3.7	21.2	23.9	6.9	21.5	10.7
## 1845	25.7	43.6	43.3	56.9	47.8	31.1	30.6	32.3	29.6	40.7	39.4
## 1846	38.7	51.0	63.9	69.2	59.9	65.1	46.5	54.8	107.1	55.9	60.4
## 1847	62.6	44.9	85.7	44.7	75.4	85.3	52.2	140.6	161.2	180.4	138.9
## 1848	159.1	111.8	108.9	107.1	102.2	123.8	139.2	132.5	100.3	132.4	114.6
## 1849	156.7	131.7	96.5	102.5	80.6	81.2	78.0	61.3	93.7	71.5	99.7
## 1850	78.0	89.4	82.6	44.1	61.6	70.0	39.1	61.6	86.2	71.0	54.8
## 1851	75.5	105.4	64.6	56.5	62.6	63.2	36.1	57.4	67.9	62.5	50.9
## 1852	68.4	67.5	61.2	65.4	54.9	46.9	42.0	39.7	37.5	67.3	54.3
## 1853	41.1	42.9	37.7	47.6	34.7	40.0	45.9	50.4	33.5	42.3	28.8
## 1854	15.4	20.0	20.7	26.4	24.0	21.1	18.7	15.8	22.4	12.7	28.2
## 1855	12.3	11.4	17.4	4.4	9.1	5.3	0.4	3.1	0.0	9.7	4.3
## 1856	0.5	4.9	0.4	6.5	0.0	5.0	4.6	5.9	4.4	4.5	7.7
## 1857	13.7	7.4	5.2	11.1	29.2	16.0	22.2	16.9	42.4	40.6	31.4
## 1858	39.0	34.9	57.5	38.3	41.4	44.5	56.7	55.3	80.1	91.2	51.9
## 1859	83.7	87.6	90.3	85.7	91.0	87.1	95.2	106.8	105.8	114.6	97.2
## 1860	81.5	88.0	98.9	71.4	107.1	108.6	116.7	100.3	92.2	90.1	97.9
## 1861	62.3	77.8	101.0	98.5	56.8	87.8	78.0	82.5	79.9	67.2	53.7
## 1862	63.1	64.5	43.6	53.7	64.4	84.0	73.4	62.5	66.6	42.0	50.6
## 1863	48.3	56.7	66.4	40.6	53.8	40.8	32.7	48.1	22.0	39.9	37.7
## 1864	57.7	47.1	66.3	35.8	40.6	57.8	54.7	54.8	28.5	33.9	57.6
## 1865	48.7	39.3	39.5	29.4	34.5	33.6	26.8	37.8	21.6	17.1	24.6
## 1866	31.6	38.4	24.6	17.6	12.9	16.5	9.3	12.7	7.3	14.1	9.0
## 1867	0.0	0.7	9.2	5.1	2.9	1.5	5.0	4.9	9.8	13.5	9.3
## 1868	15.6	15.8	26.5	36.6	26.7	31.1	28.6	34.4	43.8	61.7	59.1
## 1869	60.9	59.3	52.7	41.0	104.0	108.4	59.2	79.6	80.6	59.4	77.4
## 1870	77.3	114.9	159.4	160.0	176.0	135.6	132.4	153.8	136.0	146.4	147.5
## 1871	88.3	125.3	143.2	162.4	145.5	91.7	103.0	110.0	80.3	89.0	105.4
## 1872	79.5	120.1	88.4	102.1	107.6	109.9	105.5	92.9	114.6	103.5	112.0
## 1873	86.7	107.0	98.3	76.2	47.9	44.8	66.9	68.2	47.5	47.4	55.4
## 1874	60.8	64.2	46.4	32.0	44.6	38.2	67.8	61.3	28.0	34.3	28.9
## 1875	14.6	22.2	33.8	29.1	11.5	23.9	12.5	14.6	2.4	12.7	17.7
## 1876	14.3	15.0	31.2	2.3	5.1	1.6	15.2	8.8	9.9	14.3	9.9
## 1877	24.4	8.7	11.7	15.8	21.2	13.4	5.9	6.3	16.4	6.7	14.5
## 1878	3.3	6.0	7.8	0.1	5.8	6.4	0.1	0.0	5.3	1.1	4.1
## 1879	0.8	0.6	0.0	6.2	2.4	4.8	7.5	10.7	6.1	12.3	12.9
## 1880	24.0	27.5	19.5	19.3	23.5	34.1	21.9	48.1	66.0	43.0	30.7
## 1881	36.4	53.2	51.5	51.7	43.5	60.5	76.9	58.0	53.2	64.0	54.8
## 1882	45.0	69.3	67.5	95.8	64.1	45.2	45.4	40.4	57.7	59.2	84.4

## 1883	60.6	46.9	42.8	82.1	32.1	76.5	80.6	46.0	52.6	83.8	84.5
## 1884	91.5	86.9	86.8	76.1	66.5	51.2	53.1	55.8	61.9	47.8	36.6
## 1885	42.8	71.8	49.8	55.0	73.0	83.7	66.5	50.0	39.6	38.7	33.3
## 1886	29.9	25.9	57.3	43.7	30.7	27.1	30.3	16.9	21.4	8.6	0.3
## 1887	10.3	13.2	4.2	6.9	20.0	15.7	23.3	21.4	7.4	6.6	6.9
## 1888	12.7	7.1	7.8	5.1	7.0	7.1	3.1	2.8	8.8	2.1	10.7
## 1889	0.8	8.5	7.0	4.3	2.4	6.4	9.7	20.6	6.5	2.1	0.2
## 1890	5.3	0.6	5.1	1.6	4.8	1.3	11.6	8.5	17.2	11.2	9.6
## 1891	13.5	22.2	10.4	20.5	41.1	48.3	58.8	33.2	53.8	51.5	41.9
## 1892	69.1	75.6	49.9	69.6	79.6	76.3	76.8	101.4	62.8	70.5	65.4
## 1893	75.0	73.0	65.7	88.1	84.7	88.2	88.8	129.2	77.9	79.7	75.1
## 1894	83.2	84.6	52.3	81.6	101.2	98.9	106.0	70.3	65.9	75.5	56.6
## 1895	63.3	67.2	61.0	76.9	67.5	71.5	47.8	68.9	57.7	67.9	47.2
## 1896	29.0	57.4	52.0	43.8	27.7	49.0	45.0	27.2	61.3	28.4	38.0
## 1897	40.6	29.4	29.1	31.0	20.0	11.3	27.6	21.8	48.1	14.3	8.4
## 1898	30.2	36.4	38.3	14.5	25.8	22.3	9.0	31.4	34.8	34.4	30.9
## 1899	19.5	9.2	18.1	14.2	7.7	20.5	13.5	2.9	8.4	13.0	7.8
## 1900	9.4	13.6	8.6	16.0	15.2	12.1	8.3	4.3	8.3	12.9	4.5
## 1901	0.2	2.4	4.5	0.0	10.2	5.8	0.7	1.0	0.6	3.7	3.8
## 1902	5.2	0.0	12.4	0.0	2.8	1.4	0.9	2.3	7.6	16.3	10.3
## 1903	8.3	17.0	13.5	26.1	14.6	16.3	27.9	28.8	11.1	38.9	44.5
## 1904	31.6	24.5	37.2	43.0	39.5	41.9	50.6	58.2	30.1	54.2	38.0
## 1905	54.8	85.8	56.5	39.3	48.0	49.0	73.0	58.8	55.0	78.7	107.2
## 1906	45.5	31.3	64.5	55.3	57.7	63.2	103.6	47.7	56.1	17.8	38.9
## 1907	76.4	108.2	60.7	52.6	42.9	40.4	49.7	54.3	85.0	65.4	61.5
## 1908	39.2	33.9	28.7	57.6	40.8	48.1	39.5	90.5	86.9	32.3	45.5
## 1909	56.7	46.6	66.3	32.3	36.0	22.6	35.8	23.1	38.8	58.4	55.8
## 1910	26.4	31.5	21.4	8.4	22.2	12.3	14.1	11.5	26.2	38.3	4.9
## 1911	3.4	9.0	7.8	16.5	9.0	2.2	3.5	4.0	4.0	2.6	4.2
## 1912	0.3	0.0	4.9	4.5	4.4	4.1	3.0	0.3	9.5	4.6	1.1
## 1913	2.3	2.9	0.5	0.9	0.0	0.0	1.7	0.2	1.2	3.1	0.7
## 1914	2.8	2.6	3.1	17.3	5.2	11.4	5.4	7.7	12.7	8.2	16.4
## 1915	23.0	42.3	38.8	41.3	33.0	68.8	71.6	69.6	49.5	53.5	42.5
## 1916	45.3	55.4	67.0	71.8	74.5	67.7	53.5	35.2	45.1	50.7	65.6
## 1917	74.7	71.9	94.8	74.7	114.1	114.9	119.8	154.5	129.4	72.2	96.4
## 1918	96.0	65.3	72.2	80.5	76.7	59.4	107.6	101.7	79.9	85.0	83.4
## 1919	48.1	79.5	66.5	51.8	88.1	111.2	64.7	69.0	54.7	52.8	42.0
## 1920	51.1	53.9	70.2	14.8	33.3	38.7	27.5	19.2	36.3	49.6	27.2
## 1921	31.5	28.3	26.7	32.4	22.2	33.7	41.9	22.8	17.8	18.2	17.8
## 1922	11.8	26.4	54.7	11.0	8.0	5.8	10.9	6.5	4.7	6.2	7.4
## 1923	4.5	1.5	3.3	6.1	3.2	9.1	3.5	0.5	13.2	11.6	10.0
## 1924	0.5	5.1	1.8	11.3	20.8	24.0	28.1	19.3	25.1	25.6	22.5
## 1925	5.5	23.2	18.0	31.7	42.8	47.5	38.5	37.9	60.2	69.2	58.6
## 1926	71.8	70.0	62.5	38.5	64.3	73.5	52.3	61.6	60.8	71.5	60.5
## 1927	81.6	93.0	69.6	93.5	79.1	59.1	54.9	53.8	68.4	63.1	67.2
## 1928	83.5	73.5	85.4	80.6	76.9	91.4	98.0	83.8	89.7	61.4	50.3
## 1929	68.9	64.1	50.2	52.8	58.2	71.9	70.2	65.8	34.4	54.0	81.1
## 1930	65.3	49.2	35.0	38.2	36.8	28.8	21.9	24.9	32.1	34.4	35.6
## 1931	14.6	43.1	30.0	31.2	24.6	15.3	17.4	13.0	19.0	10.0	18.7
## 1932	12.1	10.6	11.2	11.2	17.9	22.2	9.6	6.8	4.0	8.9	8.2

## 1933	12.3	22.2	10.1	2.9	3.2	5.2	2.8	0.2	5.1	3.0	0.6
## 1934	3.4	7.8	4.3	11.3	19.7	6.7	9.3	8.3	4.0	5.7	8.7
## 1935	18.9	20.5	23.1	12.2	27.3	45.7	33.9	30.1	42.1	53.2	64.2
## 1936	62.8	74.3	77.1	74.9	54.6	70.0	52.3	87.0	76.0	89.0	115.4
## 1937	132.5	128.5	83.9	109.3	116.7	130.3	145.1	137.7	100.7	124.9	74.4
## 1938	98.4	119.2	86.5	101.0	127.4	97.5	165.3	115.7	89.6	99.1	122.2
## 1939	80.3	77.4	64.6	109.1	118.3	101.0	97.6	105.8	112.6	88.1	68.1
## 1940	50.5	59.4	83.3	60.7	54.4	83.9	67.5	105.5	66.5	55.0	58.4
## 1941	45.6	44.5	46.4	32.8	29.5	59.8	66.9	60.0	65.9	46.3	38.3
## 1942	35.6	52.8	54.2	60.7	25.0	11.4	17.7	20.2	17.2	19.2	30.7
## 1943	12.4	28.9	27.4	26.1	14.1	7.6	13.2	19.4	10.0	7.8	10.2
## 1944	3.7	0.5	11.0	0.3	2.5	5.0	5.0	16.7	14.3	16.9	10.8
## 1945	18.5	12.7	21.5	32.0	30.6	36.2	42.6	25.9	34.9	68.8	46.0
## 1946	47.6	86.2	76.6	75.7	84.9	73.5	116.2	107.2	94.4	102.3	123.8
## 1947	115.7	113.4	129.8	149.8	201.3	163.9	157.9	188.8	169.4	163.6	128.0
## 1948	108.5	86.1	94.8	189.7	174.0	167.8	142.2	157.9	143.3	136.3	95.8
## 1949	119.1	182.3	157.5	147.0	106.2	121.7	125.8	123.8	145.3	131.6	143.5
## 1950	101.6	94.8	109.7	113.4	106.2	83.6	91.0	85.2	51.3	61.4	54.8
## 1951	59.9	59.9	59.9	92.9	108.5	100.6	61.5	61.0	83.1	51.6	52.4
## 1952	40.7	22.7	22.0	29.1	23.4	36.4	39.3	54.9	28.2	23.8	22.1
## 1953	26.5	3.9	10.0	27.8	12.5	21.8	8.6	23.5	19.3	8.2	1.6
## 1954	0.2	0.5	10.9	1.8	0.8	0.2	4.8	8.4	1.5	7.0	9.2
## 1955	23.1	20.8	4.9	11.3	28.9	31.7	26.7	40.7	42.7	58.5	89.2
## 1956	73.6	124.0	118.4	110.7	136.6	116.6	129.1	169.6	173.2	155.3	201.3
## 1957	165.0	130.2	157.4	175.2	164.6	200.7	187.2	158.0	235.8	253.8	210.9
## 1958	202.5	164.9	190.7	196.0	175.3	171.5	191.4	200.2	201.2	181.5	152.3
## 1959	217.4	143.1	185.7	163.3	172.0	168.7	149.6	199.6	145.2	111.4	124.0
## 1960	146.3	106.0	102.2	122.0	119.6	110.2	121.7	134.1	127.2	82.8	89.6
## 1961	57.9	46.1	53.0	61.4	51.0	77.4	70.2	55.9	63.6	37.7	32.6
## 1962	38.7	50.3	45.6	46.4	43.7	42.0	21.8	21.8	51.3	39.5	26.9
## 1963	19.8	24.4	17.1	29.3	43.0	35.9	19.6	33.2	38.8	35.3	23.4
## 1964	15.3	17.7	16.5	8.6	9.5	9.1	3.1	9.3	4.7	6.1	7.4
## 1965	17.5	14.2	11.7	6.8	24.1	15.9	11.9	8.9	16.8	20.1	15.8
## 1966	28.2	24.4	25.3	48.7	45.3	47.7	56.7	51.2	50.2	57.2	57.2
## 1967	110.9	93.6	111.8	69.5	86.5	67.3	91.5	107.2	76.8	88.2	94.3
## 1968	121.8	111.9	92.2	81.2	127.2	110.3	96.1	109.3	117.2	107.7	86.0
## 1969	104.4	120.5	135.8	106.8	120.0	106.0	96.8	98.0	91.3	95.7	93.5
## 1970	111.5	127.8	102.9	109.5	127.5	106.8	112.5	93.0	99.5	86.6	95.2
## 1971	91.3	79.0	60.7	71.8	57.5	49.8	81.0	61.4	50.2	51.7	63.2
## 1972	61.5	88.4	80.1	63.2	80.5	88.0	76.5	76.8	64.0	61.3	41.6
## 1973	43.4	42.9	46.0	57.7	42.4	39.5	23.1	25.6	59.3	30.7	23.9
## 1974	27.6	26.0	21.3	40.3	39.5	36.0	55.8	33.6	40.2	47.1	25.0
## 1975	18.9	11.5	11.5	5.1	9.0	11.4	28.2	39.7	13.9	9.1	19.4
## 1976	8.1	4.3	21.9	18.8	12.4	12.2	1.9	16.4	13.5	20.6	5.2
## 1977	16.4	23.1	8.7	12.9	18.6	38.5	21.4	30.1	44.0	43.8	29.1
## 1978	51.9	93.6	76.5	99.7	82.7	95.1	70.4	58.1	138.2	125.1	97.9
## 1979	166.6	137.5	138.0	101.5	134.4	149.5	159.4	142.2	188.4	186.2	183.3
## 1980	159.6	155.0	126.2	164.1	179.9	157.3	136.3	135.4	155.0	164.7	147.9
## 1981	114.0	141.3	135.5	156.4	127.5	90.0	143.8	158.7	167.3	162.4	137.5
## 1982	111.2	163.6	153.8	122.0	82.2	110.4	106.1	107.6	118.8	94.7	98.1

[illegible]

## 1797	3.0
## 1798	9.9
## 1799	8.6
## 1800	40.1
## 1801	48.2
## 1802	50.0
## 1803	48.0
## 1804	60.0
## 1805	38.3
## 1806	24.0
## 1807	0.0
## 1808	12.3
## 1809	0.0
## 1810	0.0
## 1811	1.1
## 1812	10.1
## 1813	14.3
## 1814	20.1
## 1815	65.0
## 1816	29.9
## 1817	28.4
## 1818	25.8
## 1819	30.6
## 1820	9.7
## 1821	0.0
## 1822	0.0
## 1823	20.4
## 1824	0.8
## 1825	22.0
## 1826	68.1
## 1827	46.1
## 1828	46.6
## 1829	56.5
## 1830	82.1
## 1831	28.9
## 1832	27.5
## 1833	9.9
## 1834	34.5
## 1835	77.5
## 1836	206.2
## 1837	129.8
## 1838	79.8
## 1839	63.6
## 1840	53.7
## 1841	38.8
## 1842	17.6
## 1843	12.7
## 1844	21.6
## 1845	59.7
## 1846	65.5

##	1847	109.6
##	1848	159.9
##	1849	97.0
##	1850	60.0
##	1851	71.4
##	1852	45.4
##	1853	23.4
##	1854	21.4
##	1855	3.1
##	1856	7.2
##	1857	37.2
##	1858	66.9
##	1859	81.0
##	1860	95.6
##	1861	80.5
##	1862	40.9
##	1863	41.2
##	1864	28.6
##	1865	12.8
##	1866	1.5
##	1867	25.2
##	1868	67.6
##	1869	104.3
##	1870	130.0
##	1871	90.3
##	1872	83.9
##	1873	49.2
##	1874	29.3
##	1875	9.9
##	1876	8.2
##	1877	2.3
##	1878	0.5
##	1879	7.2
##	1880	29.6
##	1881	47.3
##	1882	41.8
##	1883	75.9
##	1884	47.2
##	1885	21.7
##	1886	12.4
##	1887	20.7
##	1888	6.7
##	1889	6.7
##	1890	7.8
##	1891	32.3
##	1892	78.6
##	1893	93.8
##	1894	60.0
##	1895	70.7
##	1896	42.6

##	1897	33.3
##	1898	12.6
##	1899	10.5
##	1900	0.3
##	1901	0.0
##	1902	1.1
##	1903	45.6
##	1904	54.6
##	1905	55.5
##	1906	64.7
##	1907	47.3
##	1908	39.5
##	1909	54.2
##	1910	5.8
##	1911	2.2
##	1912	6.4
##	1913	3.8
##	1914	22.3
##	1915	34.5
##	1916	53.0
##	1917	129.3
##	1918	59.2
##	1919	34.9
##	1920	29.9
##	1921	20.3
##	1922	17.5
##	1923	2.8
##	1924	16.5
##	1925	98.6
##	1926	79.4
##	1927	45.2
##	1928	59.0
##	1929	108.0
##	1930	25.8
##	1931	17.8
##	1932	11.0
##	1933	0.3
##	1934	15.4
##	1935	61.5
##	1936	123.4
##	1937	88.8
##	1938	92.7
##	1939	42.1
##	1940	68.3
##	1941	33.7
##	1942	22.5
##	1943	18.8
##	1944	28.4
##	1945	27.4
##	1946	121.7

```
## 1947 116.5
## 1948 138.0
## 1949 117.6
## 1950 54.1
## 1951 45.8
## 1952 34.3
## 1953 2.5
## 1954 7.6
## 1955 76.9
## 1956 192.1
## 1957 239.4
## 1958 187.6
## 1959 125.0
## 1960 85.6
## 1961 40.0
## 1962 23.2
## 1963 14.9
## 1964 15.1
## 1965 17.0
## 1966 70.4
## 1967 126.4
## 1968 109.8
## 1969 97.9
## 1970 83.5
## 1971 82.2
## 1972 45.3
## 1973 23.3
## 1974 20.5
## 1975 7.8
## 1976 15.3
## 1977 43.2
## 1978 122.7
## 1979 176.3
## 1980 174.4
## 1981 150.1
## 1982 127.0
## 1983 33.4
```

```
library(timeSeries)
```

```
## Warning: package 'timeSeries' was built under R version 3.5.3
```

```
## Loading required package: timeDate
```

```
library(xts)
```

```
## Warning: package 'xts' was built under R version 3.5.3
```

```
## Loading required package: zoo
```

```
##
## Attaching package: 'zoo'

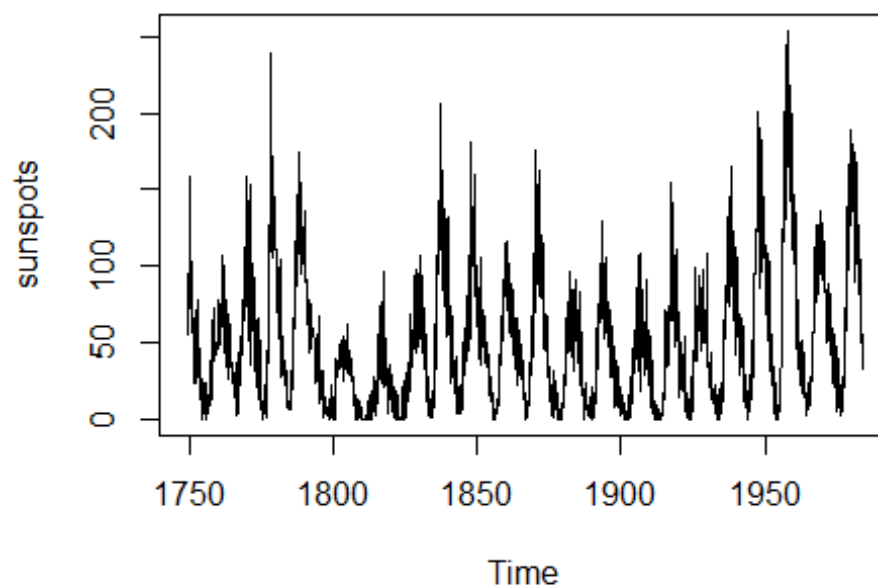
## The following object is masked from 'package:timeSeries':
##
##   time<-

## The following objects are masked from 'package:base':
##
##   as.Date, as.Date.numeric

library(forecast)

## Warning: package 'forecast' was built under R version 3.5.3

plot(sunspots)
```



```
class(sunspots)

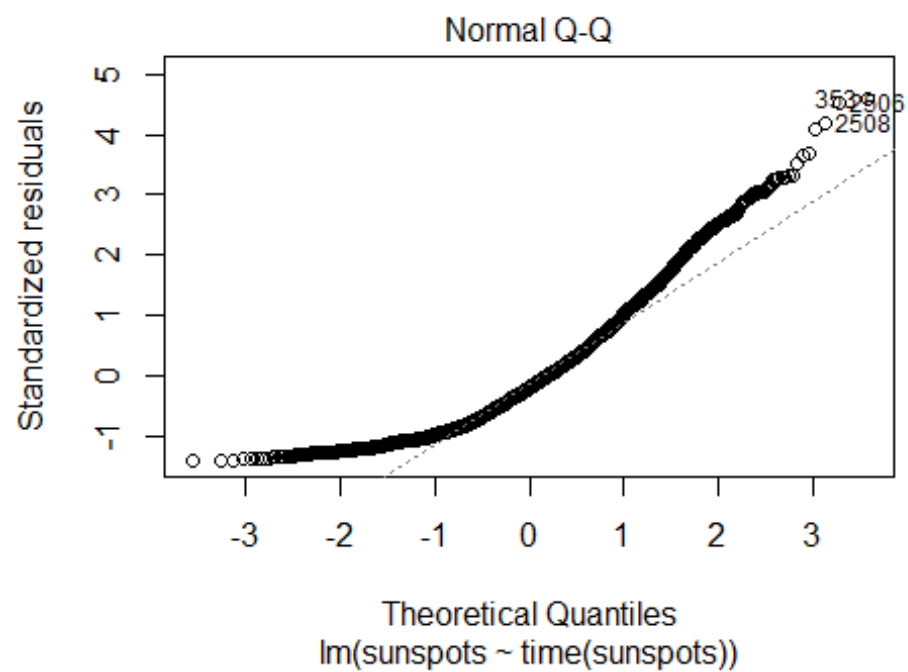
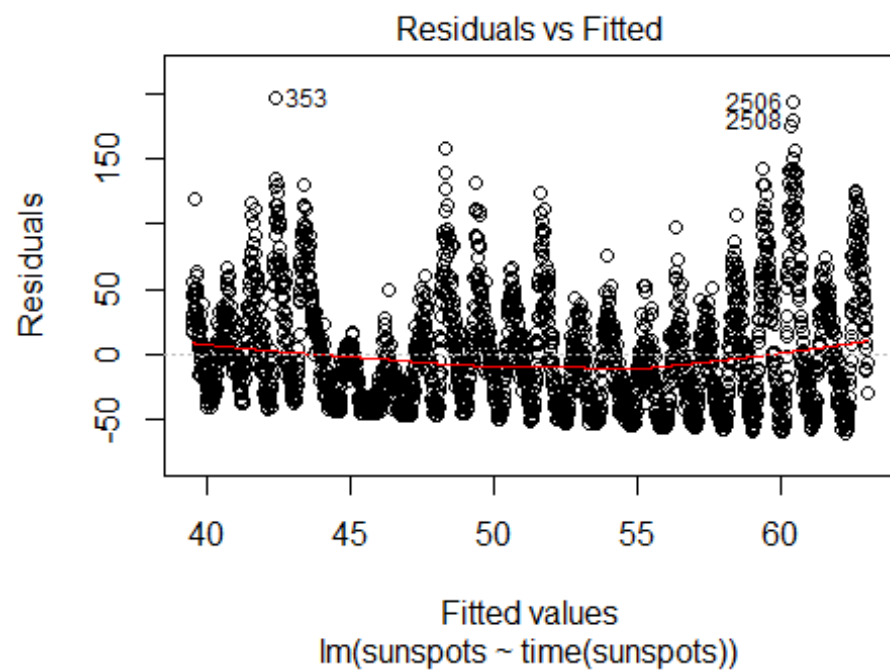
## [1] "ts"

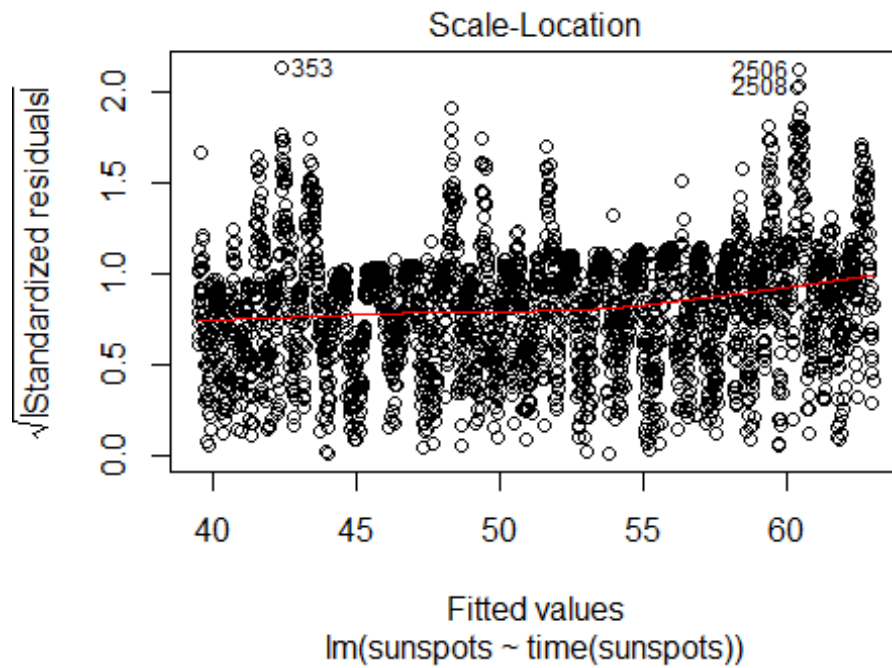
#cycle(sunspots)

frequency(sunspots)

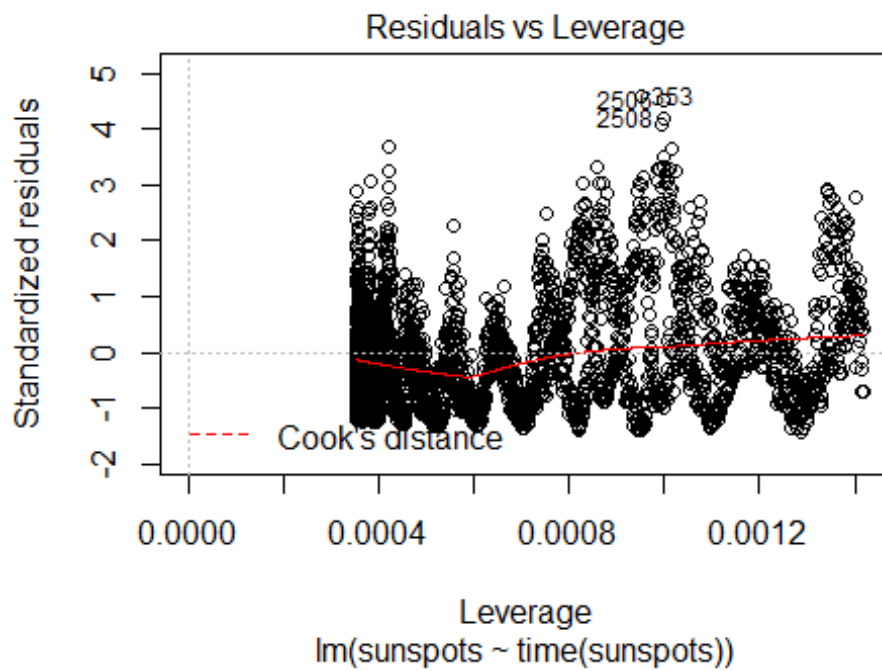
## [1] 12

m <- lm(sunspots ~ time(sunspots))
plot(m)
```

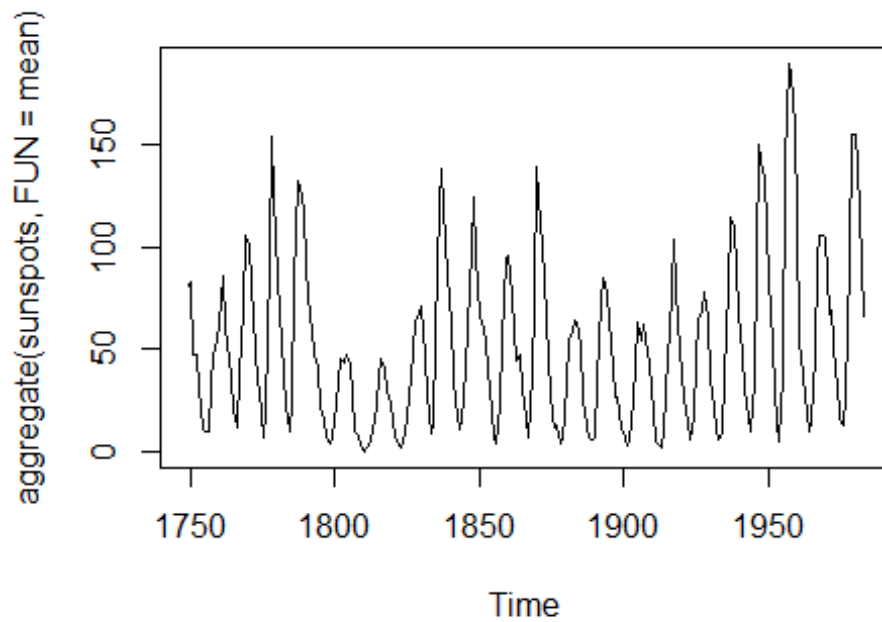




```
abline(m)
```

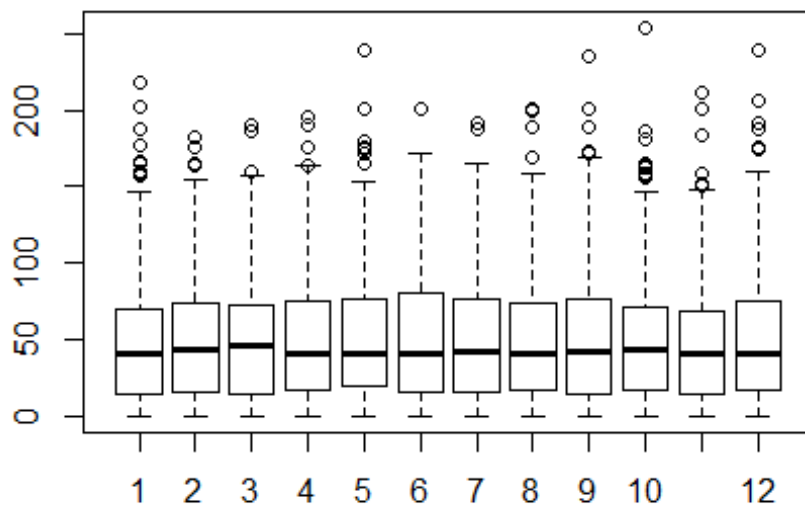


```
plot(aggregate(sunspots, FUN = mean))
```



Q. Plot the monthly (or other suitable periodic) boxplots

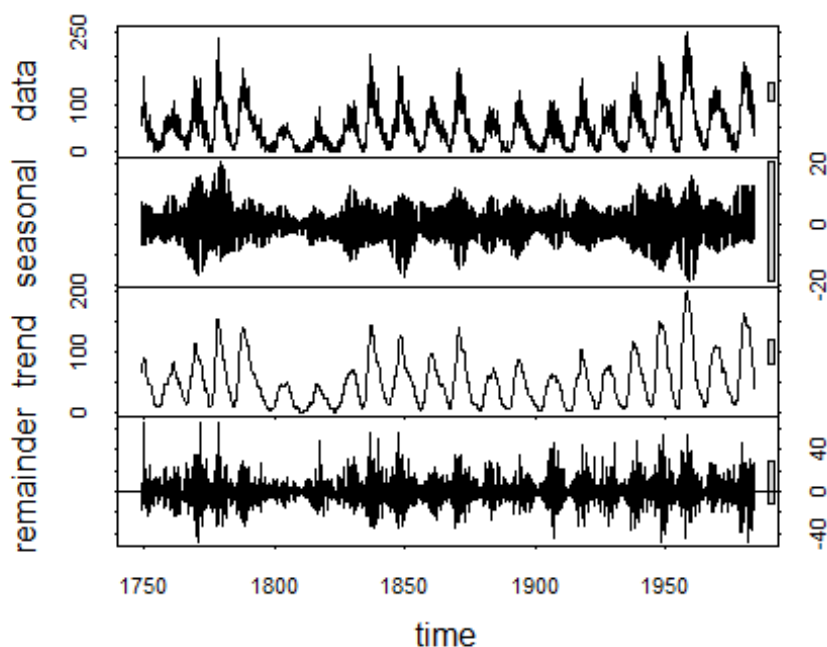
```
boxplot(sunspots ~ cycle(sunspots))
```



Q. Decompose the time series using the stl function. What type of trend does it show?

Answer: The plot is showing yearly seasonal trend.

```
d <- stl(sunspots, s.window = 12)
plot(d)
```



Q. What type of seasonality?

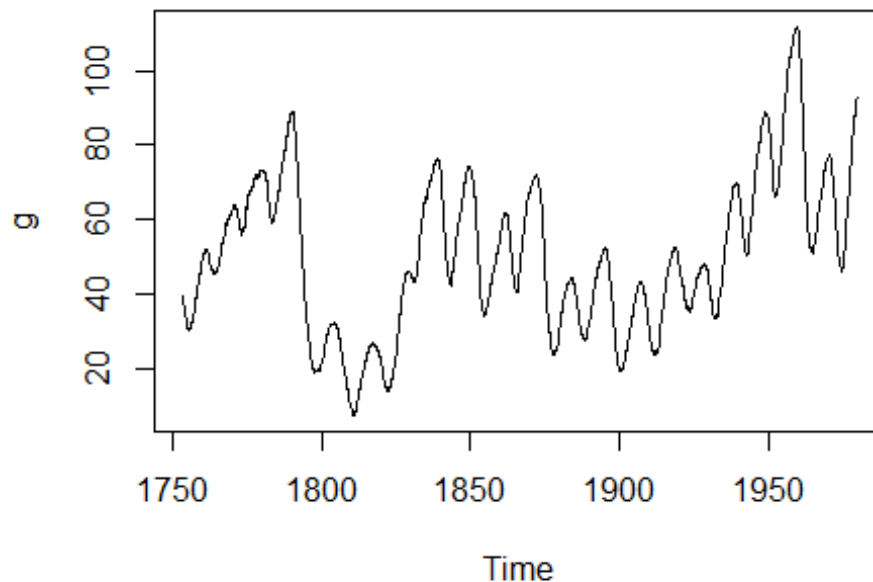
Answer: Seasonality is a characteristic of a time series in which the data experiences regular and predictable changes that recur every calendar year. Any predictable fluctuation or pattern that recurs or repeats over a one-year period is said to be seasonal.

Seasonal effects are different from cyclical effects, as seasonal cycles are observed within one calendar year, while cyclical effects, such as boosted sales due to low unemployment rates, can span time periods shorter or longer than one calendar year.

Q. How is the residue after you remove trend and seasonality?

Answer: It gives the graph with “remainder” which is basically showing noise. There are periodic ups and downs.

```
mean(sunspots)
## [1] 51.26596
g <- rollmean(sunspots, k = 100)
plot(g)
```



Q. Build a model of the data using the HoltWinters method for the period upto about 75% of the data (e.g., up to December 2015 if it were for the CO2 data set). Use suitable values of alpha, beta and gamma.

```
require(graphics)

library(zoo)
sunspots_zoo <- as.zoo(sunspots)
zoo_75 <- sunspots_zoo[1:2112]
zoo_25 <- sunspots_zoo[2113:length(sunspots)]

df_75 <- as.ts(zoo_75)
```



```
df_25 <- as.ts(zoo_25)
#df_25
```

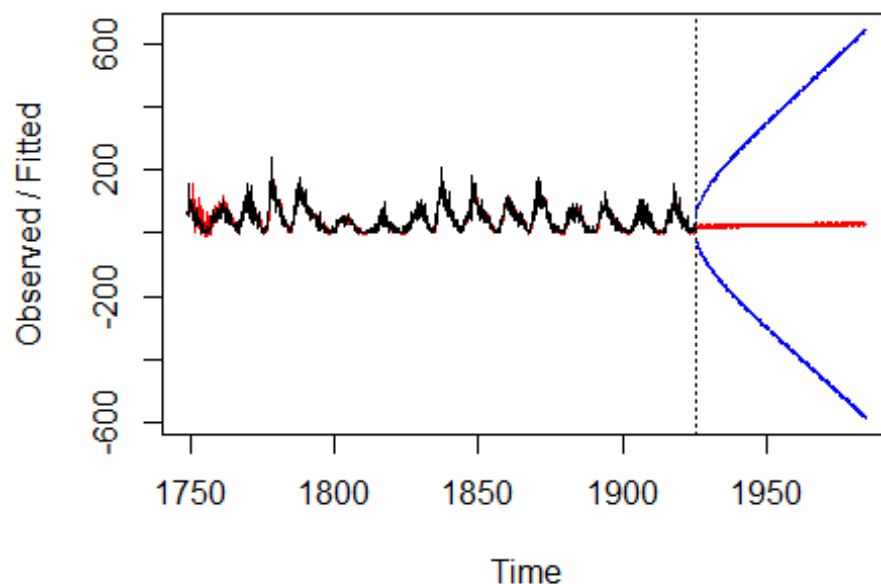
**Q. Try to fine tune the model by changing alpha, beta and gamma.
Are you able to improve the model (i.e., get a lower rms error)?**

```
sunspotsPredict <- HoltWinters(df_75, alpha = 0.4856207, beta = 0.001282363,  
gamma = 0.1589522)
```

Q. Predict the values for the next 25% of the time (e.g., for the CO2 data set, all of 2016 and the first 3 months of 2017).

```
p <- predict(sunspotsPredict, 708, prediction.interval = TRUE)  
plot(sunspotsPredict, p)
```

Holt-Winters filtering



```

#p
p_zoo <- as.zoo(p)

p_df <- p[, 'fit']

#p_df <- subset(p, select = c(fit))
#p_df

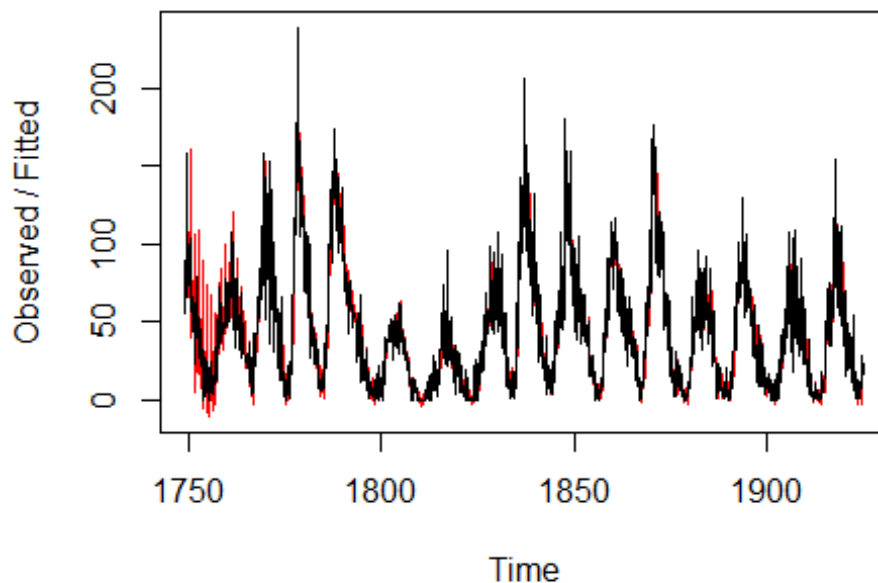
class(p_df)

## [1] "ts"

plot(sunspotsPredict)

```

Holt-Winters filtering



Q. Plot the predicted values along with the actual values to compare them.

```

fitted <- matrix(p_df, ncol = 12, byrow = FALSE)
#fitted

matrix_df_25 <- as.matrix(df_25)
#matrix_df_25
actual <- matrix(matrix_df_25, ncol = 12, byrow = FALSE)
#actual

```

```
#rms <- actual - fitted
#rms
```

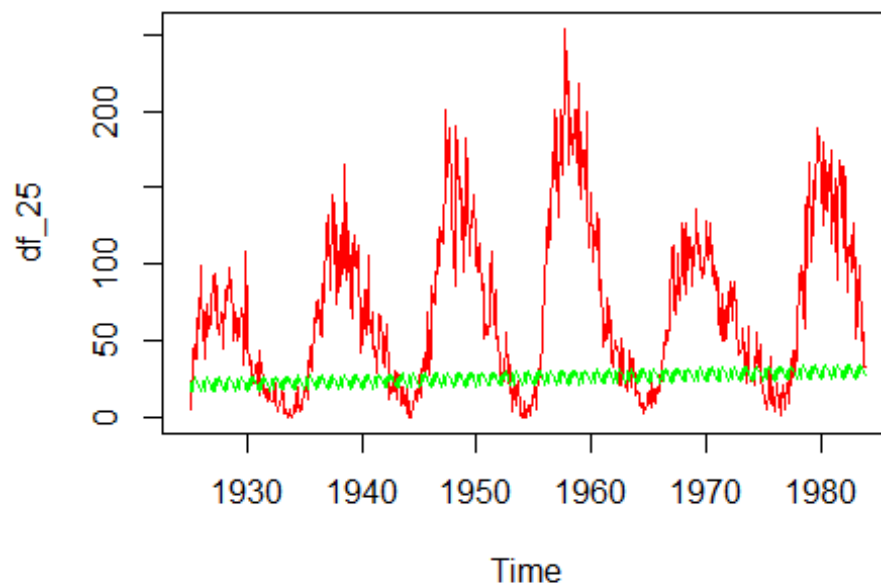
Q. Compute the rms error between the predicted and actual values.

```
RMSE = function(fitted, actual){
  sqrt(mean((fitted - actual)^2))
}
```

```
RMSE(fitted, actual)
```

```
## [1] 68.75884
```

```
plot(df_25, col = "red")
lines(p_zoo$fit, col = "green")
```



```
class(df_75)
```

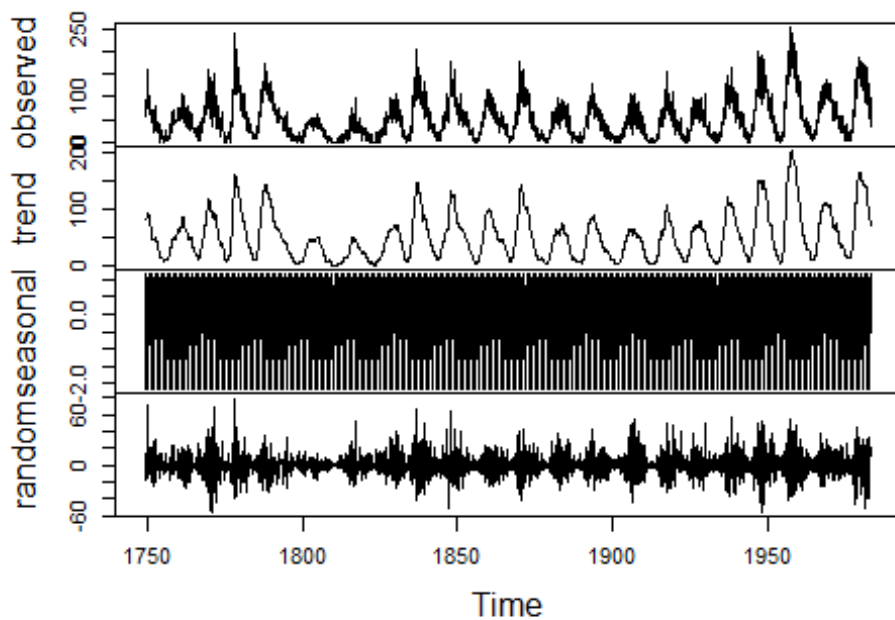
```
## [1] "ts"
```

```
library(forecast)
```

```
components.ts = decompose(sunspots)
```

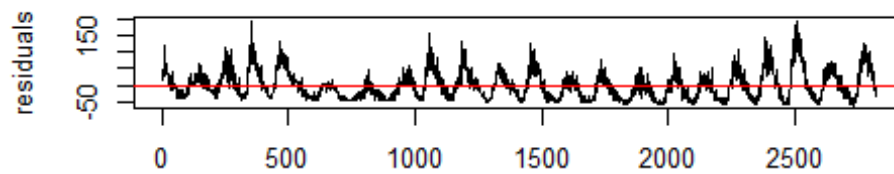
```
plot(components.ts)
```

Decomposition of additive time series

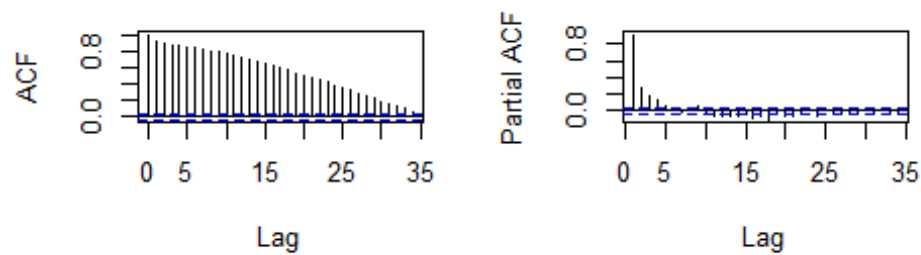


```
library("fUnitRoots")  
## Warning: package 'fUnitRoots' was built under R version 3.5.3  
## Loading required package: fBasics  
## Warning: package 'fBasics' was built under R version 3.5.3  
urkpssTest(sunspots, type = c("tau"), lags = c("short"), use.lag = NULL,  
doplot = TRUE)
```

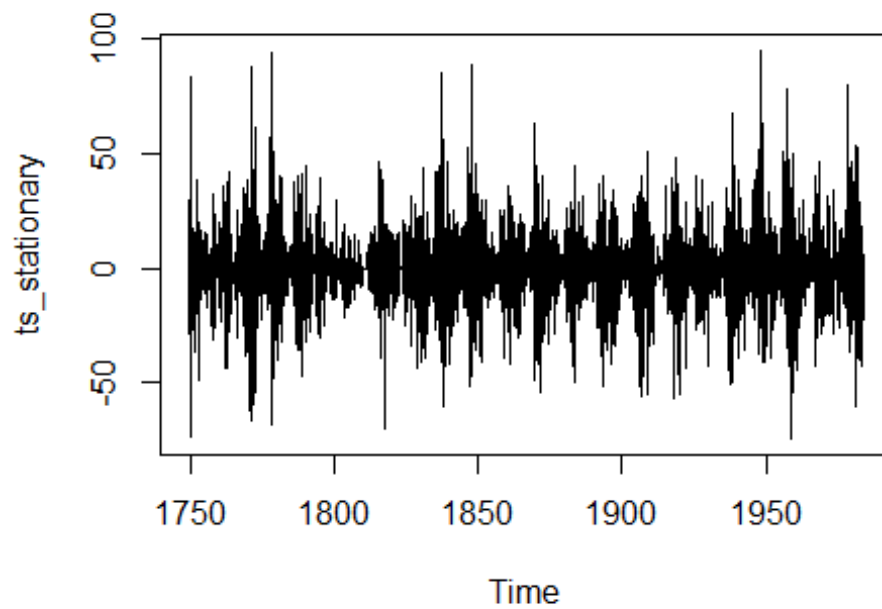
Residuals from test regression of type: tau with 9 lags



Autocorrelations of Residual Partial Autocorrelations of Resid

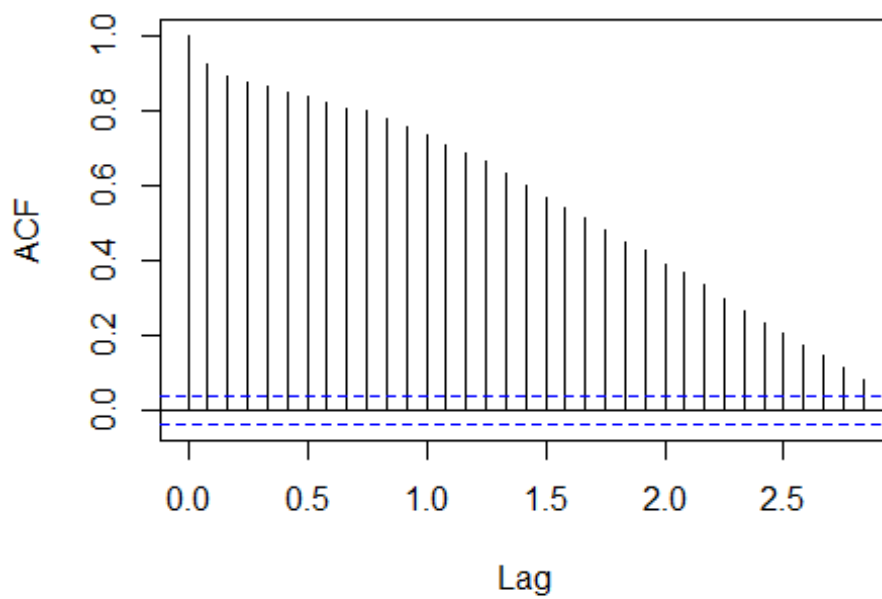


```
##
## Title:
## KPSS Unit Root Test
##
## Test Results:
## NA
##
## Description:
## Fri May 03 15:33:17 2019 by user: IIIIT
ts_stationary = diff(sunspots, differences=1)
plot(ts_stationary)
```



#autoCorrelation : no linear association between observations separated by larger lags
`acf(sunspots, lag.max = 34)`

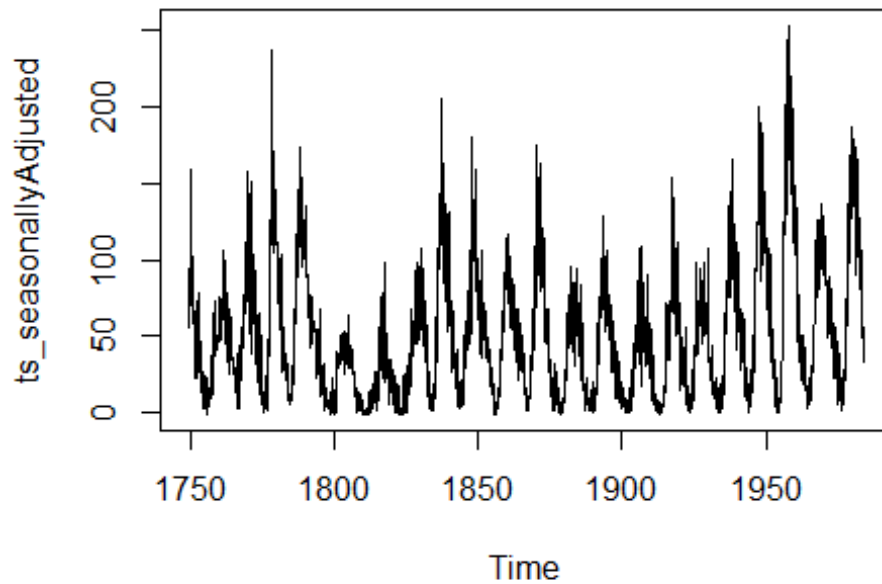
Series sunspots



#Remove seasonality from the original series

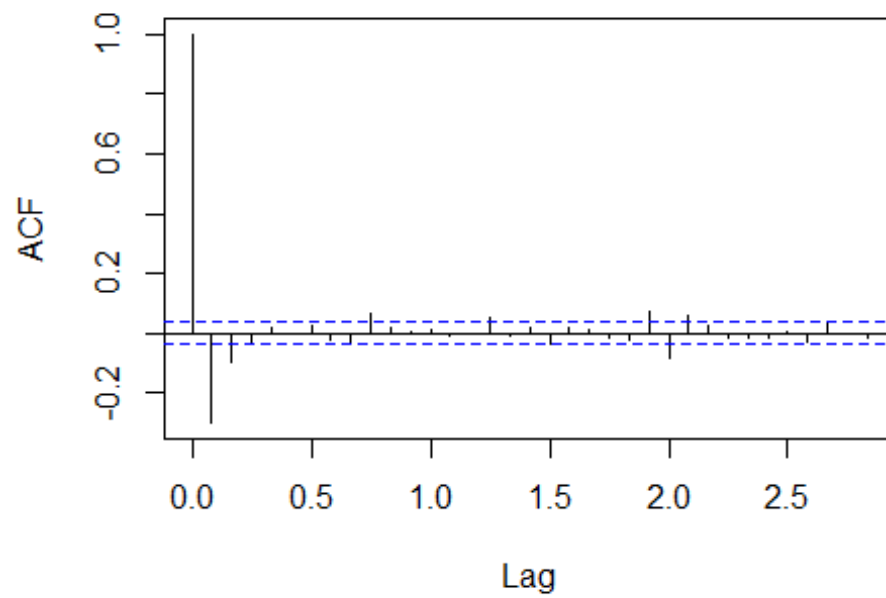
```
ts_seasonallyAdjusted <- sunspots - components.ts$seasonal  
ts_stationary <- diff(ts_seasonallyAdjusted, differences=1)
```

```
plot(ts_seasonallyAdjusted)
```



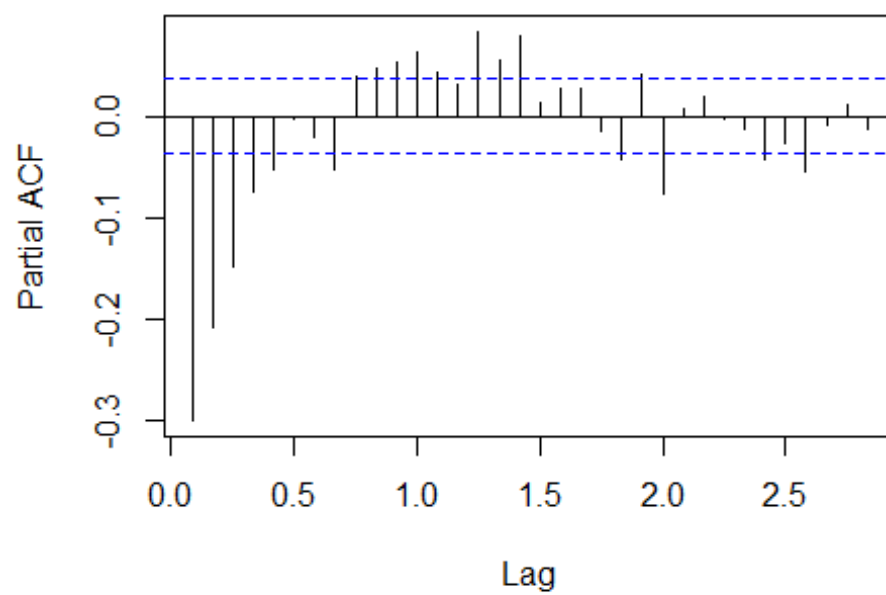
```
acf(ts_stationary, lag.max = 34)
```

Series ts_stationary



```
pacf(ts_stationary, lag.max = 34)
```

Series ts_stationary



Q. Build an ARIMA model for the period up to about 75% of the data (e.g., for the CO2 data, up to December 2015) using auto.arima()

```
#order: non-seasonal part(p, d, q)
#seasonal: seasonal part of ARIMA
#method: fitting model
fitARIMA <- arima(df_75, order=c(1,1,1),seasonal = list(order = c(1,0,0),
period = 12),method="ML")
library(lmtest)
coeftest(fitARIMA)

##
## z test of coefficients:
##
##      Estimate Std. Error  z value  Pr(>|z|)
## ar1    0.216614   0.035463   6.1082 1.007e-09 ***
## ma1   -0.666507   0.025750  -25.8839 < 2.2e-16 ***
## sar1    0.041316   0.022328   1.8504  0.06425 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

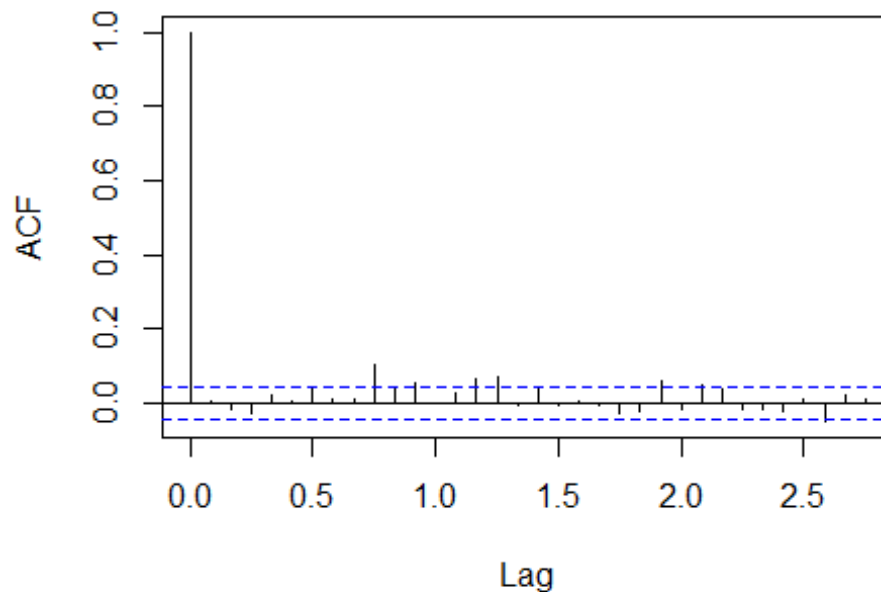
confint(fitARIMA)

##              2.5 %       97.5 %
## ar1    0.147108523  0.28611988
## ma1   -0.716975463 -0.61603784
## sar1  -0.002445492  0.08507695

acf(fitARIMA$residuals)
```

Q. Predict the values for the next 15 months (e.g., for the CO2 data, all of 2016 and the first 3 months of 2017).

Series fitARIMA\$residuals

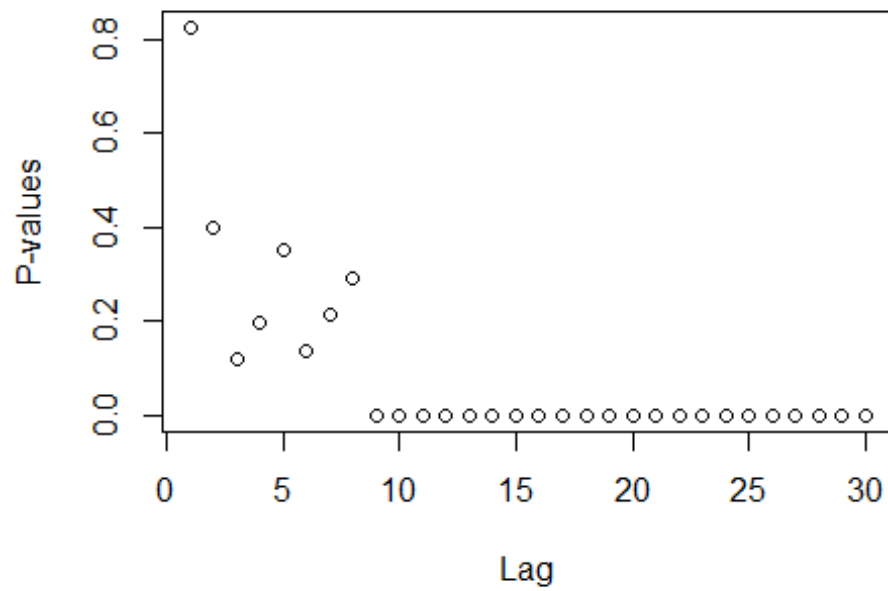


```
library(FitAR)

## Warning: package 'FitAR' was built under R version 3.5.3
## Loading required package: lattice
## Loading required package: leaps
## Warning: package 'leaps' was built under R version 3.5.3
## Loading required package: ltsa
## Loading required package: bestglm
## Warning: package 'bestglm' was built under R version 3.5.3
##
## Attaching package: 'FitAR'
##
## The following object is masked from 'package:forecast':
##
##      BoxCox

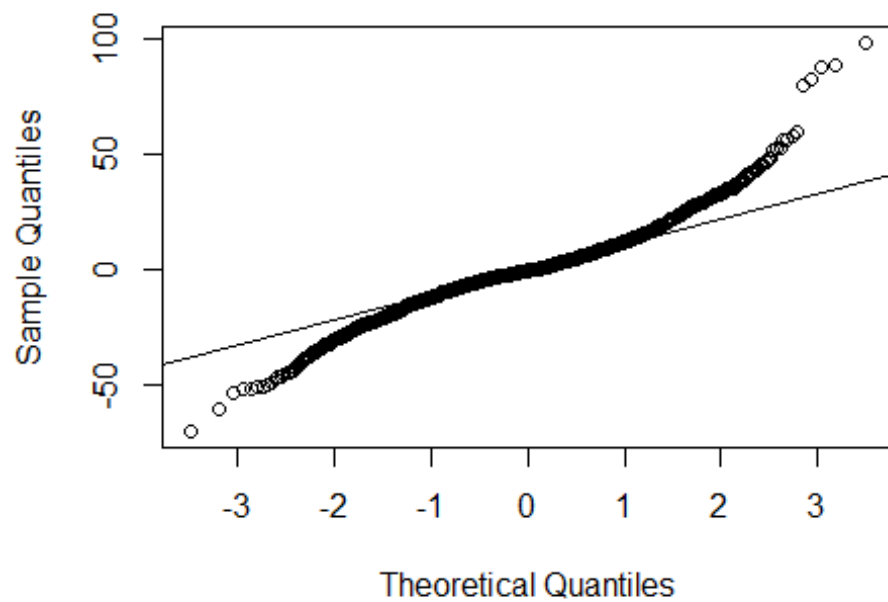
boxresult<-LjungBoxTest (fitARIMA$residuals,k = 2, StartLag = 1)
plot(boxresult[,3],main= "Ljung-Box Q Test", ylab= "P-values", xlab= "Lag")
```

Ljung-Box Q Test



```
qqnorm(fitARIMA$residuals)  
qqline(fitARIMA$residuals)
```

Normal Q-Q Plot



```

auto.arima(df_75, trace=TRUE)

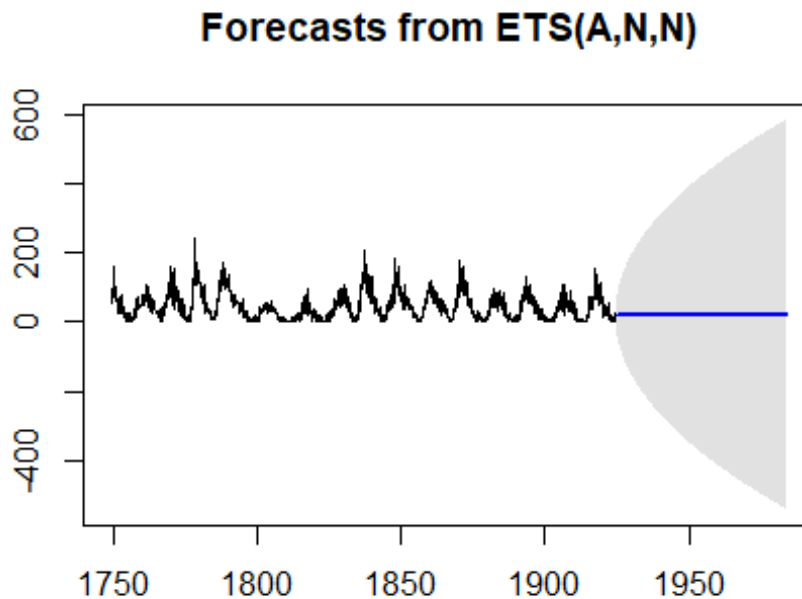
##
## Fitting models using approximations to speed things up...
##
## ARIMA(2,0,2)(1,0,1)[12] with non-zero mean : 17413.4
## ARIMA(0,0,0) with non-zero mean : 21324.77
## ARIMA(1,0,0)(1,0,0)[12] with non-zero mean : 17715.03
## ARIMA(0,0,1)(0,0,1)[12] with non-zero mean : 19186.54
## ARIMA(0,0,0) with zero mean : 23183.14
## ARIMA(2,0,2)(0,0,1)[12] with non-zero mean : 17445.62
## ARIMA(2,0,2)(1,0,0)[12] with non-zero mean : 17412.53
## ARIMA(2,0,2) with non-zero mean : 17447.78
## ARIMA(2,0,2)(2,0,0)[12] with non-zero mean : 17414.74
## ARIMA(2,0,2)(2,0,1)[12] with non-zero mean : 17416.74
## ARIMA(1,0,2)(1,0,0)[12] with non-zero mean : 17410.08
## ARIMA(1,0,2) with non-zero mean : 17445.4
## ARIMA(1,0,2)(2,0,0)[12] with non-zero mean : 17414.76
## ARIMA(1,0,2)(1,0,1)[12] with non-zero mean : 17411.24
## ARIMA(1,0,2)(0,0,1)[12] with non-zero mean : 17443.33
## ARIMA(1,0,2)(2,0,1)[12] with non-zero mean : 17416.18
## ARIMA(0,0,2)(1,0,0)[12] with non-zero mean : 18537.75
## ARIMA(1,0,1)(1,0,0)[12] with non-zero mean : 17437.63
## ARIMA(1,0,3)(1,0,0)[12] with non-zero mean : 17411.74
## ARIMA(0,0,1)(1,0,0)[12] with non-zero mean : 18964.08
## ARIMA(0,0,3)(1,0,0)[12] with non-zero mean : 18351.77
## ARIMA(2,0,1)(1,0,0)[12] with non-zero mean : 17411.83
## ARIMA(2,0,3)(1,0,0)[12] with non-zero mean : 17413.13
## ARIMA(1,0,2)(1,0,0)[12] with zero mean : Inf
##
## Now re-fitting the best model(s) without approximations...
##
## ARIMA(1,0,2)(1,0,0)[12] with non-zero mean : 17444.48
##
## Best model: ARIMA(1,0,2)(1,0,0)[12] with non-zero mean

## Series: df_75
## ARIMA(1,0,2)(1,0,0)[12] with non-zero mean
##
## Coefficients:
##          ar1          ma1          ma2          sar1          mean
##          0.9806    -0.4383    -0.1127    0.0454    44.7247
## s.e.    0.0046     0.0220     0.0205    0.0225     7.7248
##
## sigma^2 estimated as 225.3: log likelihood=-8716.22
## AIC=17444.44 AICc=17444.48 BIC=17478.37

arimaPred <- predict(fitARIMA,n.ahead = 708)
futurVal <- forecast(df_75,h=708, level=c(99.5))

```

```
#forecast(futurVal)
plot(futurVal)
```



```
#Arima RMSE
```

Q. Compute the rms error between the predicted and actual values.

```
diffArima <- (sqrt(mean((df_25 - arimaPred$pred)^2)))
diffArima
## [1] 72.69348
```

**Q. Based on your experiment, which method is better and why?
HoltWinters or ARIMA?**

Answer: In my case HoltWinters method has given better results than ARIMA. The rms error in HoltWinters was 68 whereas it was 72 in case of ARIMA.